AD-A170 284 SARSAT OPERATIONAL DATA CATEGORIZATION AND ACCURACY STUDIES(U) DEFENCE RESEARCH ESTABLISHMENT OTTAWA (ONTARIO) W R MCPHERSON ET AL. SEP 85 DREO-TN-85-26 1/1

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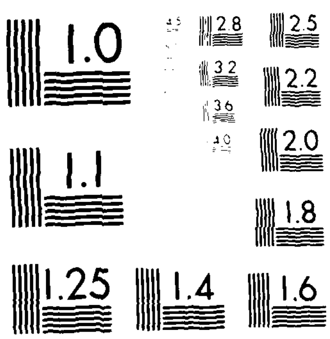

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AD-A170 284

SARSAT OPERATIONAL DATA CATEGORIZATION AND ACCURACY STUDIES

by

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DEFENCE RESEARCH ESTABLISHMENT OTTAWA
TECHNICAL NOTE 85-26

PCN
33X00

September 1985
Ottawa

ABSTRACT

The definition of what data is transferred from the SARSAT ground tracking station to operational search and rescue users influences how well the users can action beacon alert data. Based on an evaluation of operational search and rescue incident data collected during the SARSAT Demonstration and Evaluation, categorization and accuracy studies described herein indicate that methodologies can be developed which will significantly improve the operational actioning of SARSAT generated beacon alert data. The results of these studies are presented and recommended approaches to the handling of SARSAT data are given.

RÉSUMÉ

Le transfert des données depuis la station de poursuite terrestre SARSAT jusqu'aux usagers du système de recherche et de sauvetage opérationnels influe de façon importante sur le succès qu'auront les usagers dans l'utilisation des données d'alerte. En fonction d'une évaluation des données d'incident en matière de recherche et de sauvetage recueillies lors d l'étape de la démonstration et de l'évaluation du système SARSAT, les études de catégorisation et de précision décrites ci-après révèlent la possibilité d'établir des méthodologies qui contribueront de façon importante à améliorer l'usage opérationnel des données d'alerte émanant du système SARSAT. Les résultats de ces études sont présentés et des méthodes sont également recommandées sur la façon d'utiliser les données SARSAT.

A-1

SARSAT OPERATIONAL DATA

CATEGORIZATION AND ACCURACY STUDIES

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LIST OF ABBREVIATIONS

CMCC	CANADIAN MISSION CONTROL CENTRE
CTA	CROSS TRACK ANGLE
D&E	DEMONSTRATION AND EVALUATION
ELT	EMERGENCY LOCATOR TRANSMITTER
EPIRB	EMERGENCY POSITION INDICATING RADIO BEACON
LUT	LOCAL USER TERMINAL
MCC	MISSION CONTROL CENTRE
RCC	RESCUE COORDINATION CENTRE
SAR	SEARCH AND RESCUE
SEF	SARSAT EVALUATION FACILITY

1.0 INTRODUCTION

The transfer of beacon alert data from the SARSAT Local User Terminal (LUT) to the Canadian Mission Control Centre (CMCC) was the subject of a previous study, see Reference (1). The current studies expand on this initial work, and using data collected during the SARSAT Demonstration and Evaluation (D&E), assess the impact of employing data categorization schemes to support the actioning by the Search and Rescue (SAR) community of those SAR incidents either initiated or supported by SARSAT alert data.

A detailed review and analysis of operational SAR incidents involving the use of SARSAT data collected during the SARSAT D&E, i.e. during the period February 1983 to June 1984, was carried out and provided the basis for defining and evaluating these data categorization schemes. The SAR incidents necessarily of primary interest for such studies were the traced beacon transmissions. In these incidents, the actual location of the beacon was derived and hence categorization studies could be supported by accuracy of location studies.

The SARSAT operational data categorization and accuracy studies are discussed in terms of the background to the problem, an outline of approach and analytical tools developed, a presentation of the results of the analysis of the available operational data, and a discussion of these results in terms of procedures for the operational actioning of SARSAT data. Summary comments and recommendations are provided.

2.0 BACKGROUND

The SARSAT system and the companion international COSPAS-SARSAT project are described in detail in numerous documents, see Reference (2) and (3), and therefore, only a summary of the system concept is presented as background to the current studies. This is followed by a brief review of the perceived operational data handling problems which initiated the current work. With this background in place, the specific objectives of the data categorization and accuracy studies are defined.

2.1 SARSAT FACILITY OVERVIEW

The basic concept of the SARSAT satellite-aided search and rescue mission is illustrated in Figure 1. The signal radiated by an emergency beacon, either an Emergency Locator Transmitter (ELT) or an Emergency Position Indicating Radio Beacon (EPIRB), is detected by a polar-orbiting spacecraft equipped with suitable receivers. Such signals are then relayed to a SARSAT ground tracking station or Local User Terminal where the signals are processed to determine the location of the ELT or EPIRB. The fact that an alert has been detected, along with the location of the ELT or EPIRB, is then relayed via a Mission Control Centre (MCC) to an appropriate Rescue Coordination Centre (RCC) for initiation of the search and rescue activities.

Doppler-positioning, using the relative motion between the spacecraft and the ELT/EPIRB, was considered as a practical means of locating these very simple beacons. All that is required of the ELT/EPIRB is that it emit a carrier frequency with a reasonable stability during the period of mutual ELT/EPIRB-satellite visibility. To optimize Doppler-positioning performance, satellites in a low-altitude polar orbit are used. The low altitude results in low ELT/EPIRB power requirements, good Doppler-shift characteristics and short time delays between successive passes. The polar orbit results in coverage of the whole earth.

Within the context of the current discussion, the system consists of the following subsystems:

- The first subsystem is the ELT and EPIRB. These small emergency transmitters are designed to transmit distress signals in the 121.5 and 243 MHz bands.

- The second subsystem is the spacecraft (SARSAT and/or COSPAS) which receive these signals and retransmit them at 1544.5 MHz to the ground station for processing.

- The third subsystem is the ground segment facilities which consists of the LUT which receives the relayed distress signals, process them to derive a location estimate, the MCC which receives these data and then distributes them for operational actioning by the SAR users at the RCC.

The studies discussed herein focus on the activities in the third subsystem. Specifically, the problem being addressed is associated with the definition of the transfer of distress data from the LUT to the Canadian MCC and the handling of these data at the CMCC.

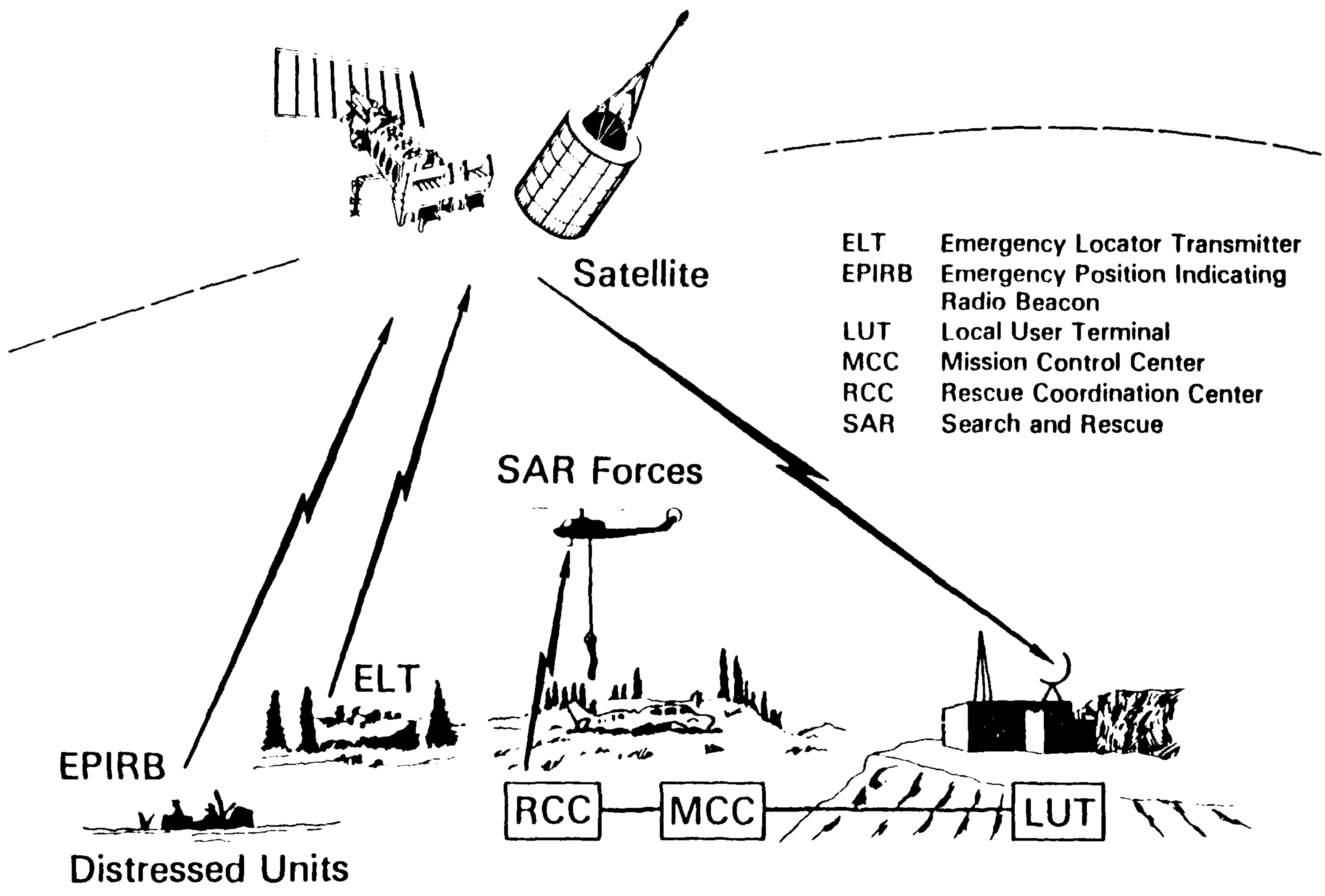


Figure 1: Basic Concept

2.2 STATEMENT OF THE PROBLEM

At Reference (1), it was noted that the problem existing at the operational level with regard to SARSAT alert information was one of a lack of data quantities being associated with location estimates. Alert data generated by the SARSAT LUT is transferred through to the CMCC for operational actioning with very little guidance provided on the quality of the data. The user is forced to treat all SARSAT data in the same manner. The CMCC operators and the RCC controllers cannot measure their response to the alert data and act accordingly.

The SARSAT system can produce very accurate estimates of location of transmitting ELT/EPIRBs, but, it can also produce poor estimates. This range in capability is due to a large number of factors, the primary ones being the characteristics of the beacon and the beacon-to-satellite geometry. The problem, therefore, is to identify the intrinsic quality of the data given the conditions under which it was derived.

An approach was developed at Reference (1) to classify incoming SARSAT alert data and procedures were suggested for actioning these data. Furthermore, the potential impact of merging data from pass-to-pass using Kalman Filter techniques was illustrated. A LUT-to-CMCC emulator was developed and tested over a sample period using operational data. However, this work was restricted in scope because the locations of the ELT/EPIRB detections used in the study were not known. In other words, while relative improvements could be illustrated, nothing could be said about the impact on the accuracy of location estimation.

The current study, expanding on the work described at Reference (1), made use of SAR incident data in which the ELT/EPIRB had actually been found. Using such data, two areas of study could be addressed. Firstly, categorization techniques could be assessed based on the type of data currently being handled by the SARSAT users. Secondly, the impact of this categorization in terms of its meaning with regard to accuracy could be quantified.

2.3 STUDY OBJECTIVES

SARSAT operational data categorization and accuracy studies were therefore initiated to:

- Validate categorization schemes with the aid of operational SAR incident data;

- Relate developed methodologies to error of location estimation;

- Outline and recommend approaches for the actioning of SARSAT alert data.

The intention of the study was to develop and validate approaches which would allow operational personnel to recognize good, mediocre and poor estimation performance on the part of SARSAT facilities, and in quantitative terms define the meaning of such a categorization. Given this information, SARSAT users could then better define their approach to the handling of the alert data.

3.0 OUTLINE OF APPROACH AND ANALYTICAL DEVELOPMENT

The approach adopted to expand on the initial characterization of the SARSAT alert data was to develop a data base consisting of all those SAR incidents in which SARSAT played a role and in which the beacon was located. This was a different approach to that used in previous studies. In the latter case a LUT-to-CMCC emulator was developed, see Reference (4), to simulate the flow of data from the ground station to the CMCC over a period of time. All data flowing through the system was processed. For the current studies, only specific alerts, i.e. the known SAR incidents, were run through the simulator. In other words, each known incident was treated as the focus of the emulation, to the exclusion of all other alert data, and then tracked in time. Considerable effort was required to build this data base as will be described.

During the development of the data base, it was found that the data categorization schemes developed during the initial studies required expansion to cover some of the anomalous signal characteristics being observed. A review of the current scheme is provided along with the modifications made to accommodate new signal types.

A significant aspect of the current studies over that of the previous work is the fact that the location of the transmitting source was known. Therefore, studies of system accuracy under operational conditions could be carried out. However, as will be discussed, there seems to be no consistent approach within the SARSAT community for the definitions and presentations of such work. The rationale behind the approach adopted in the current studies is described.

Therefore, as background to the presentation of the results of the categorization and accuracy studies, the data base developed for these studies is described, the characterization scheme definitions are updated, and finally, the approaches taken to quantify system accuracy are discussed.

3.1 DATA BASE DEVELOPMENT

During the period of the SARSAT D&E, the SARSAT project had access to the Canadian SAR statistical data base. These data consist of the RCC's records of the information related to all logged search and rescue incidents. In order to access this computerized data base, retrieval programs were developed to identify and report those cases of particular interest to SARSAT, specifically, distress and non-distress SAR cases involving ELT/EPIRB transmissions in which SARSAT facilities played a role either as the alerting device or in a support role by confirming beacon activation. The results of these queries were passed to the project on a monthly basis for analysis. These data were used to support a number of studies, see Reference (5), but also, they provided a convenient mechanism to identify and log those SAR incidents involving SARSAT. The nature of the incident, incident time and location (if known), etc. were provided in these reports.

During the period from February 1983 to June 1984, 409 SAR incidents met the requirements noted above, i.e. SARSAT involvement and knowledge of the transmission site. On average, this equates to 24 events per month. Table 1 summarizes these data according to type.

TABLE 1

ELT/EPIRB INCIDENTS INVOLVING SARSAT DATA
FEBRUARY 1983 - JUNE 1984

	SARSAT INVOLVEMENT		SAR RESOURCES USED	
NMENT	INITIATED	ASSISTED	YES	NO
S	10	7	17	0
'ESS	244	131	217	158
	1	1	2	0
	13	2	10	5

As is evident from the data in Table 1, about 95% of the incidents were non-distress false alerts, i.e. ELT/EPIRB activations for a variety of reasons none of which included a distress or emergency situation. The resource column indicates the number of incidents in which the SAR community expended time and effort in the form of sending a craft (airplane, helicopter, rescue vessel) out to look for the transmitting beacon. Clearly, on more than one half of the incidents, search and rescue resources were used. Figure 2 illustrates the geographic distribution of these incidents.

As a routine activity during the SARSAT D&E, the project collected the LUT generated alert data and stored them on the SARSAT Evaluation Facility (SEF) data base. This data base was a time ordered structure containing SARSAT evaluation data from a variety of sources. The data of interest for the current studies were the alert data consisting of the LUT derived signal processing parameters and the estimates of location resulting from the Doppler fitting process for the 409 incidents noted above.

The SAR data and the SARSAT data were two distinct data sets which had to be integrated in the following manner. The SAR incident locations were used to query the SEF data base for the related LUT data, using a "inhouse" developed software package, LOCAT, see Reference (6) for additional detail. The basis of the query was time and location. The data obtained by LOCAT were then processed through the LUT-CMCC emulator, see Reference (1) and (4). The purpose of this process was to "purify" the data within a given satellite pass, that is, sidebands were combined by means of a distance and frequency bias criteria to produce one estimate of location within the pass for the specific beacon transmission of interest. All other transmissions detected during the particular pass were ignored.

The next step involved combining the data on a pass-to-pass basis emulating updating information coming into the CMCC. In order to do this, a number of changes had to be made to the original LUT-CMCC emulation software. The original software had been written to emulate the CMCC receiving LUT data on a continuous basis over a period of time. ELT/EPIRB transmissions were detected, subsequently confirmed on following satellite passes and eventually "aged" out of the system when no further detections occurred. For the current studies, attention was focussed on a particular transmission to the exclusion of all other transmissions within the pass. Each SAR event of interest was a separate query and emulation process.

Considerable effort was required to develop the integrity of the data base thus produced. Instances did arise wherein the data from one beacon merged with that from another beacon because the initial query time range was too wide. This was particularily true for ELT/EPIRB transmissions in or near metropolitan areas. Eventually, the only approach feasible to resolve these problems was to review the anomalous incidents on a case-by-case basis and manually edit the data using information available from the SAR incident reports.

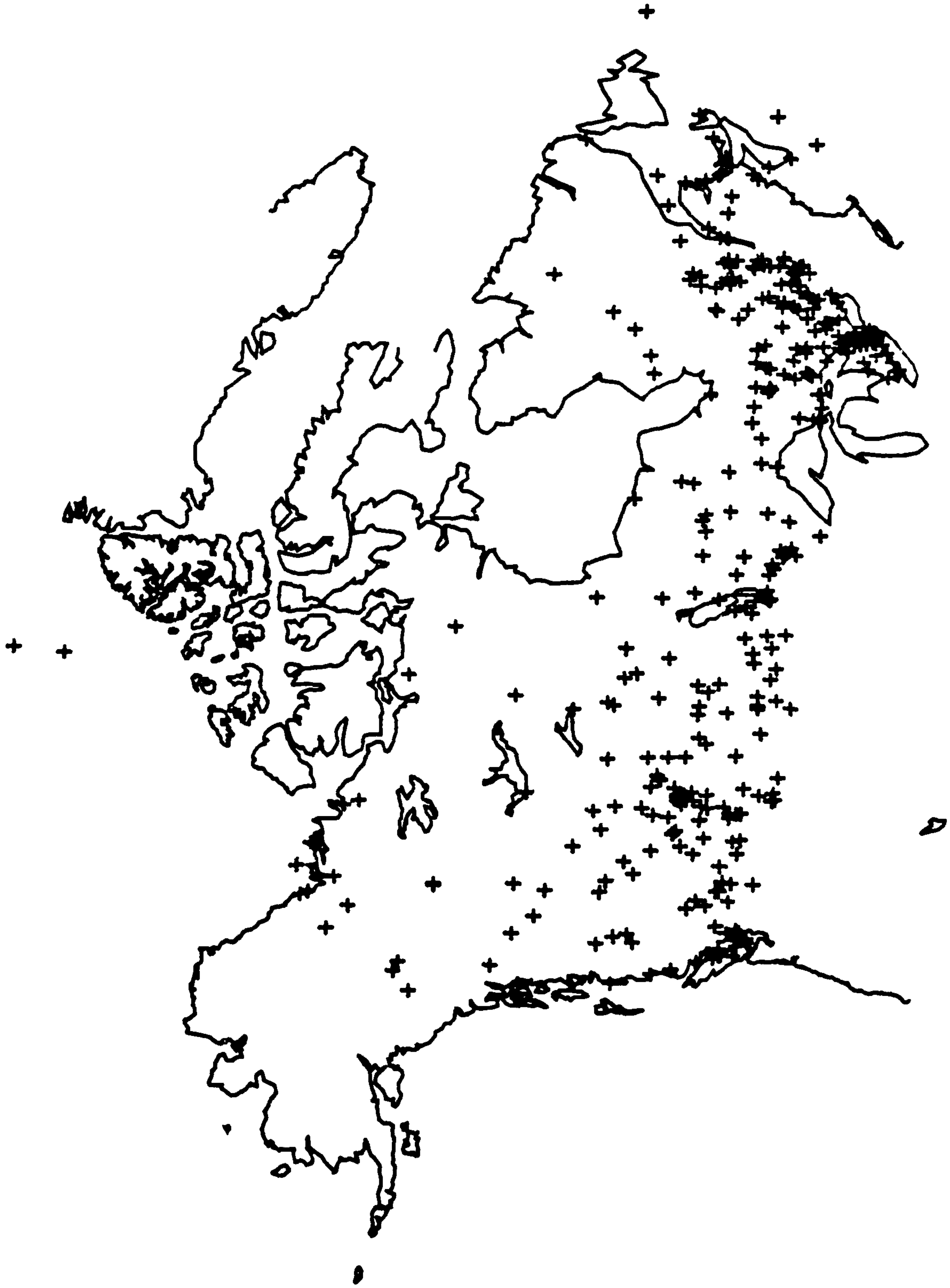


Figure 2: Geographic Distribution
SARSAT Incidents, Feb 83 - Jun 84

LUT data for 380 of the 409 incidents noted in the SAR reports to involve the participation of SARSAT were found in the SEF data base. The reasons why data for the remaining 29 incidents were not found were not established. However, a number of plausible reasons can be put forward. In all likelihood, the most probable reason why correlating SARSAT data could not be found would be that the originating SARSAT source was the USA. These data would come to Canada via the CMCC for onward transmission to the RCC's. The only data interrogated at the SEF was the Canadian LUT data. The USA data only provides location information, signal characterization data is not available. Hence it is of little use to the current studies. Another reason why events may have been missed is the fact that the data could have been so poor that it failed to meet the initial query criteria. Since the query was based on a distance criteria, there was a tradeoff in terms of making the criteria too broad and hence contaminating the data with other detections versus making the criteria too narrow and therefore missing detections.

The data base established for the categorization and accuracy studies therefore consisted of the SARSAT LUT data for 380 SAR incidents over the period of February 1983 to June 1984. A large number of these incidents involved detections on more than one satellite pass. The total number of detections for these 380 incidents was 1316 or roughly 3 detections (unique passes) per incident. These data then were the basis for the analytical studies that are discussed in the subsequent presentation.

3.2 ALERT DATA CHARACTERIZATION SCHEMES - A REVIEW AND UPDATE

The previous studies had established the SARSAT LUT-CMCC data flow. In general, the characterization of the SARSAT alert data can be reviewed as a three step activity. Firstly, all detected signals derived by the LUT as the result of a satellite pass must be organized in such a manner that one beacon transmission results in one detection. Due to the electronic characteristics of some ELTS, the LUT can derive a number of detections due to the presence of strong signal sidebands, or due to the absence of an identifiable carrier. This process of grouping the sidebands from within a specific pass is referred to as the cluster process. Once this one-to-one correspondence has been established between the transmission and the detection, a subset of the available signal processing parameters must be chosen as a representative set for the detected ELT/EPIRB. Finally, this information is transferred to the CMCC where it is compared to previous pass detections and, where appropriate, updating would occur using Kalman Filter techniques. This latter process is referred to as the merge process.

Each of these three steps are discussed.

3.2.1 The Cluster Process

The LUT cluster process is a procedure to identify all collocated transmission sources occuring on a given satellite pass. The purpose of the cluster process is twofold. Firstly, it is a mechanism to reduce the volume of extraneous data which has to be actioned by operational personnel. The cluster process has been demonstrated to reduce volume by 30%. Secondly, the cluster size has been found to be quite a useful parameter for categorizing the nature of the transmission source, given no additional information.

The initial definition of the signal type was as given in Table 2,

TABLE 2

SIGNAL TYPE CATEGORIZATION (INITIAL)

SIGNAL TYPE	CLUSTER SIZE (CL)
U	$CL = 1$
E	$1 < CL \leq 5$
I	$CL > 5$

where U implied an unknown signal (single Doppler curve), E was taken to be an ELT/EPIRB transmission with a good carrier and a number of sidebands, and I implied an interferring signal source because of the large number of transmissions radiating from the same source.

During the processing of the SAR incident data, a number of refinements had to be made to the above definition to further characterize the I type transmissions. It was found that multiple clusters were being formed from a single transmission source.

Clusters were derived for the LUT alert data based on a distance and frequency bias check. In other words, if a number of transmissions were radiating from essentially the same geographic location (within an area of 200 kilometres radius), they were assumed to come from a single source. In order to avoid the not uncommon situation of two beacons functioning in close proximity to each other, the estimated off-centre transmission frequency or the ELT/EPIRB bias was used as a characteristic signature for the beacon.

The modified logic flow employed to classify the signal type in the current studies is illustrated in Figure 3. The basic definition for the U and E type signals remained the same except that allowance was made for anomalous asymmetrical Doppler plane patterns to be classified as U type signals as discussed below.

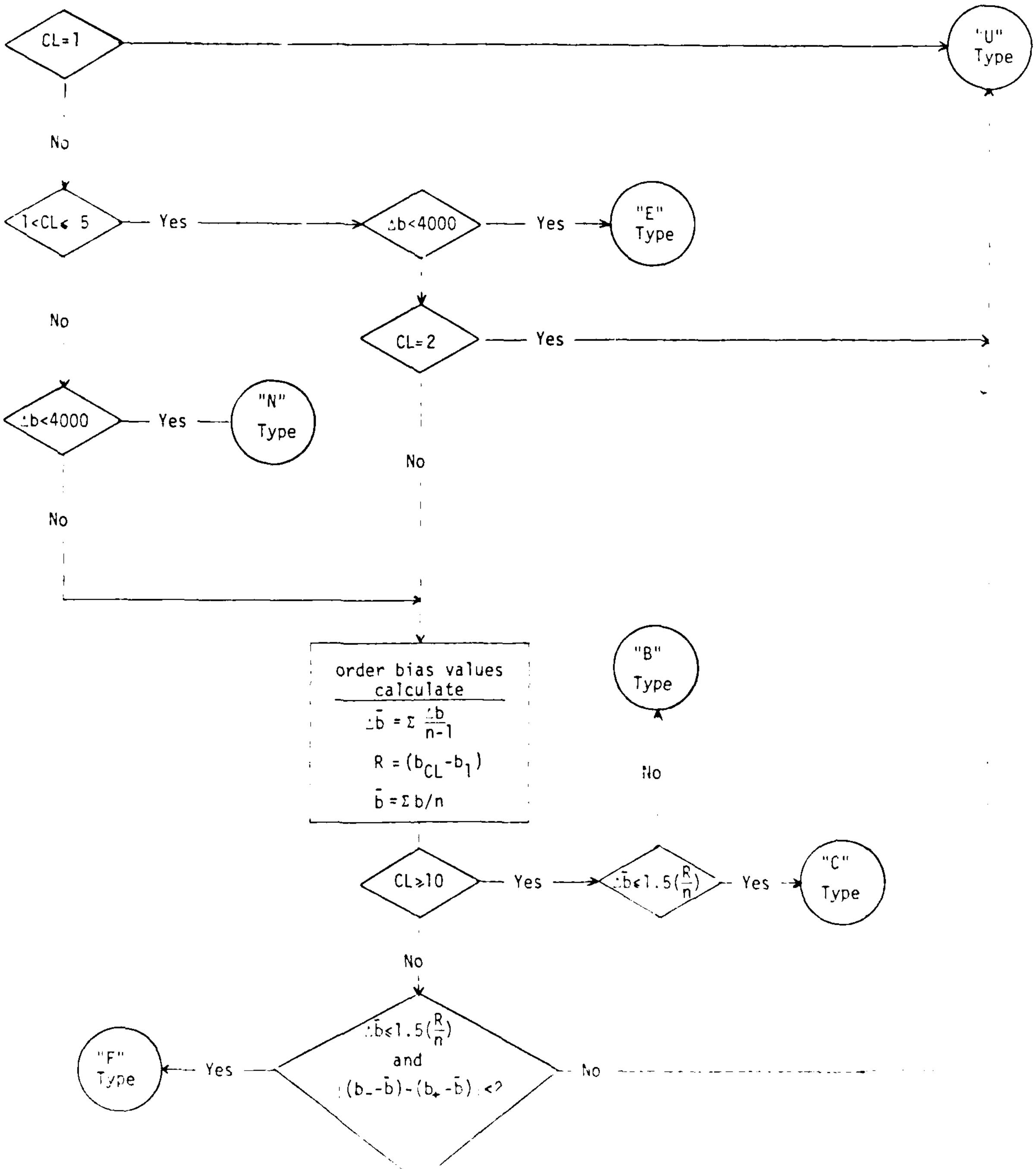


Figure 3: Signal Characterization Using Cluster Size (CL) and Bias (b).

Therefore, using the cluster size as the basic initial parameter, all transmissions wherein only one Doppler curve was identified were classed as unknown or U type signals. If the cluster size was in the range 2 to 5 and the frequency bias range was less than 4000 Hz, then the assumption was made that this was characteristic of a good ELT/EPIRB and hence the E type signal. If during the bias check, the criteria failed and the cluster size was 2, it was felt that little could be said and the signal was classified as unknown. This situation might be indicative of two poor transmitting sources in the same area.

With the exception of the last category, the above definitions are basically the original U and E type classifications. The refinements made to the I type or interference type signal consisted of definitions for N (narrow band noise), B (broad band noise), C (combing transmissions) and F, or faulty ELT transmissions.

The N type transmission was defined to be a cluster of size greater than 5 but with a narrow frequency bias range (4000 Hz). An N type transmission is really the same as an E type transmission but with more than the expected number of sidebands.

At this stage, all that remains are the anomalous Doppler plane patterns. The detections were ordered in terms of bias, the first difference was carried out on this ordered list and the bias range, R, the mean bias $\bar{b}$ and the mean bias difference calculated, i.e. $\Delta\bar{b}$. If the cluster size was greater than 10 and if the mean bias difference was approximately equal to a uniform difference ($\sim R/n$) then the signal was classified as C. The test here really was to determine whether the Doppler curves were uniformly distributed across the observed frequency range. Failing this criteria, the signal was classified as broadband noise, or B. The final signal type was the F type signal. Again, it was taken to be a Doppler plane pattern consisting of 5 to 10 curves with a uniform pattern (indigative of paired side bands). If this criteria was not met, it was classified as unknown.

During the analysis of the SAR incident data, examples of the above signal types, except for the B type signal which was a default case, were observed. Examples of the Doppler plane representatives of a C, F and N signal type are illustrated in Figure 4. While the classification of these signals was that of interferer, it should be noted that these transmissions were from ELT's which were logged as SAR incidents.

In summary, the clusters process, based on cluster size and frequency bias, categories the signals as one of the types as illustrated in Table 3.

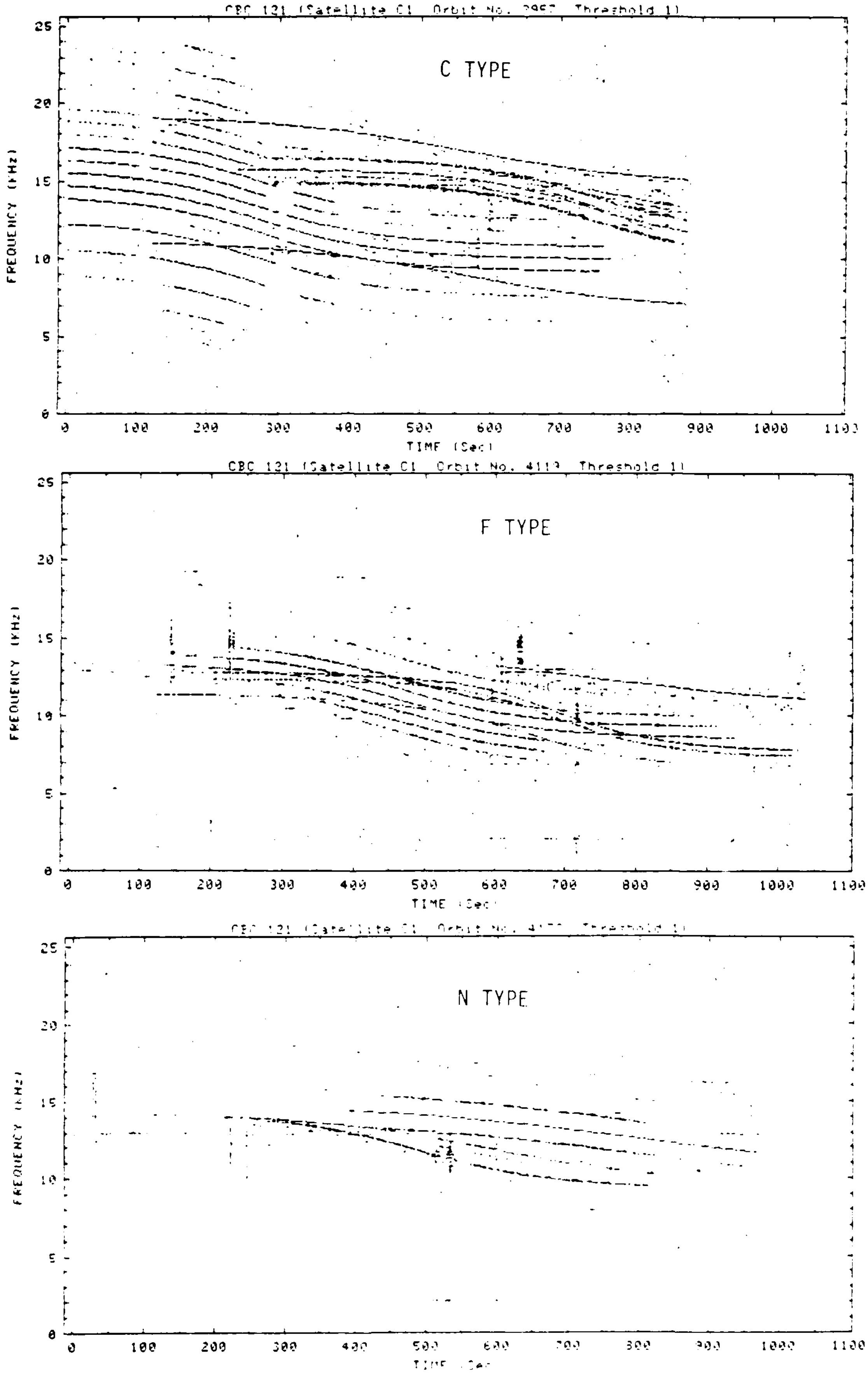


Figure 4: Sample Interference Type Signals (C, F and N)

TABLE 3

SIGNAL TYPE CATEGORIZATION (UPDATED)

SIGNAL TYPE	CLASS	CRITERIA CLUSTER SIZE	FREQUENCY BIAS DISPERSION
U	1	1	-
	2	2	> 4000 Hz
	3	< 10	Irregular
E		$1 < CL \leqslant 5$	< 4000 Hz
I	N	$CL > 5$	< 4000 Hz
	B	$CL \geqslant 10$	Irregular/Large
	C	$CL \geqslant 10$	Uniform
	F	$CL < 10$	Small, Uniform

3.2.2 Quality Parameters

At this stage of processing, the nature of the transmitting signal has been categorized. Nothing is implied about the data quality. Since the LUT Doppler processing technique is essentially a curve fitting/template matching algorithm, there is associated with each unique detection a statistical parameter set which describes the goodness-of-fit. In the case of clusters or multiple detections from the same transmission source, the criteria used to select the representative parameters which would best describe the signal was that of using the parameters associated with the first element in the cluster. The rationale for this approach was the fact that the LUT, during its Doppler processing, extracts the Doppler curves in order of signal strength. Therefore, the first element in the cluster is the strongest signal and hence can be assumed to be the carrier.

The standard deviation of the data residuals, STD measured in Hertz, has been observed from previous work (5) to correlate well with error. The following signal categorization, CAT is favoured.

TABLE 4

SIGNAL CATEGORY (CAT) DEFINITION

CATEGORY	DEFINITION (Hz)
A	$0 \leq STD \leq 8$
B	$8 < STD \leq 18$
C	$18 < STD \leq 40$
D	$STD > 40$

It is obvious that the lower the STD, the better is the match between the observed data and the theoretical Doppler curve and hence, the greater would one's confidence would be in the quality of the estimation of ELT location. Therefore a signal category of A will be better than one which is B, and a D category signal is very poor.

As the definition implies, the STD or root mean square of residuals says nothing about the amount of data used in the estimation process. One could observe a small STD based on a few data points leading to a poor estimate. Therefore, a quality factor Q was introduced as a measure of the density of the Doppler curve taking into account geometry effects. It is a measure of the amount of data in the curve relative to an ideal curve. It ranges in value from 0 to 1, one being equated as perfect in terms of data density (but not necessarily goodness-of-fit). For convenience, Q is given in terms of its quartiles. The definition of Q is provided at Reference 1 .

The argument is then made that the signal category and the Q factor are reasonable guides for assessing the quality of the SARSAT alert data. The objective of the analysis discussed in Section 4 is the development of operational rules usings the signal type, CAT and Q to guide user actioning of the alert data.

It is well understood that the ELT/EPIRB-to-satellite geometry has an impact on data quality. Overhead satellite passes give an ambiguity in the latitude estimate while beacons transmitting close to the satellite viewing horizon present problems in longitude. For the COSPAS and SARSAT satellites (altitudes in the range 800-1100 kilometres), it has been established that the system functions reasonably well in the cross-track angle (CTA) range $2° \leq CTA < 18°$. Outside this range, system performance can degrade significantly. Therefore, the procedures developed for actioning SARSAT alert data must take into account the negative impact that poor geometry has on the estimation process.

3.2.3 The Merge Process

Thus far, the discussion has focussed on categorizing the LUT alert data for a given satellite pass. However, on a large number of SAR incidents, the signal is detected on subsequent passes. This gives rise to the need to combine current pass data with previous pass data. Since the LUT Doppler processing techniques used to fit the observed data to the theoretical model are statistical procedures, i.e. least squares fitting, sufficient data is available tc support a Kalman Filter updating process, see Reference (1) for details.

In an analogus manner to the formation of clusters at the LUT, current pass detections at the CMCC can be compared to previous pass detection based on distance and frequencing bias criteria. If the match is successful, the data from the passes can be merged to form a new "best estimate" of the location of the transmitting source. In an operational scenario, this process would continue until such time as the beacon was located through SAR actioning and turned off or the owner of the ELT/EPIRB, for any number of reasons, discovered that his ELT/EPIRB was on and turned it off himself. In the latter case, the incident would be categorized as a detected but not located false alert.

The merge process gives rise to two sets of location estimates. The first set is the LUT estimates which are based solely on data from an individual satellite pass. The second is the CMCC data which are based on multiple pass detections. The latter, theoretically, will provide better location estimates. The quantitative improvement of the CMCC data over that of the LUT data for the 380 SAR incidents which form the analysis data base are discussed in Section 4.

3.3 ACCURACY MODELS

There is no consistent approach within the SARSAT community for the definition of accuracy of location estimation. One discussion, see Reference (7), attempted to classify the definition of accuracy, but to date, different evaluation teams are using different approaches.

These problems of definition occur for a number of reasons, two of which are as follows. The primary reason is related to the ambiguity arising from the initial engineering specification of performance of the LUT. As a design goal, documentation specified accuracy as 20 kilometres, one sigma. This would seem at first to be a reasonable definition given that one has a univariate, symmetrical or normal distribution of error. However, SARSAT involves detections in a region (error in latitude and longitude), obviously bivariate. The reduction of the bivariate error

model to a univariate model through the use of the radial error leads to a situation in which the specification requirement for accuracy does not make sense. The second reason why problems have occurred is that evaluators are looking for simple accuracy qualifying parameters which will describe the system in its most favourable terms. On average, SARSAT performs quite well. However, the range of performance in the operational environment is very broad, due in large measure to the poor performance characteristics of the ELT/EPIRB. In other words, as discussed previously, it can function extremely well, but also it can give quite poor performance. This latter performance then tends to bias the interpretation of system performance averages.

At Reference (7), it is argued that within geometric constraints noted previously, the SARSAT estimation process will demonstrate normally distributed errors in latitude and longitude. Furthermore, it is assumed that the magnitude of error in latitude and longitude is the same and that error is independent.

Therefore, under these assumptions it follows that, letting

$$X_e = \text{error in latitude}, \sim N(\mu x, \sigma_x)$$
$$Y_e = \text{error in longitude}, \sim N(\mu y, \sigma_y)$$

and $\sigma_x = \sigma_y = \sigma$, then if

$$r = \sqrt{X^2_e + Y^2_e}, \text{ the radial error}$$

it is quite simple to illustrate that r, the radial error is distributed as a Rayleigh distribution,

$$\text{or} \quad r \sim \frac{r}{\sigma^2} e^{-r^2/2\sigma^2}$$

The cumulative probability function for radial error less than some R then is

$$Pr(r \quad R) = 1-e^{-R^2/2\sigma^2}$$

and the first and second moments of the distribution, expressed in terms of σ are

$$\mu_r = \left(\frac{2\sigma^2}{\pi}\right)^{\frac{1}{2}}$$

$$\sigma_r^2 = 2\sigma^2 (1-1/\pi)$$

A number of problems exist in the above development. Firstly, the assumptions of error equality and independence can be questioned. It is known that the Doppler curve fitting process is more sensitive in latitude estimation than longitude estimation. Therefore, it follows that errors in latitude would be less than those in longitude. Independence is doubted in the operational environment. Work on simulation studies have suggested that the more the system departs from the ideal Doppler curve fitting situation, the weaker the assumption of error independence becomes. As is illustrated in Figure 4, the operational environment with low power ELT/EPIRB and questionable transmission characteristics is far from ideal.

Secondly, referring back to the specification for accuracy, there is an ambiguity over which sigma to use, the σ from the bivariate normal or the σ_r for the radial error.

If $R = \sigma$, then $Pr(r < R) = 0.39$, but if $R = \sigma_r$ then $Pr(r < R) = 0.49$. This is obvious that the use of σ in the specification of accuracy is liberal, only 40% of the detections need be within one sigma. On the other hand, the use of σ_r leads to a general approach in which the median of the cumulative distribution can be used.

In order to circumvent the problems noted above, the approach adopted for the analysis discussed in Section 4 was a distribution free approach. This approach requires no assumptions. Instead, observed probability distribution functions were used. Since the preferred measure of error is the radial error which in turn gives rise to an asymmetrical density function, the distribution characteristic was taken to be the median or 50 percentile. It is an easily quantifiable parameter and coincidentally closely corresponds to $Pr(r < R)$ when $R = \sigma_r$. As an added descriptor, the percentile at which error is less than 20 km is also provided as a relative measure.

4.0 ANALYTICAL RESULTS

Using the approaches discussed in Section 3, an extensive analysis was carried out on the 1316 detections resulting from the 380 SAR incidents. Firstly, the data was characterized in terms of the signal distribution and the quality parameters. Observed location error was studied in terms of this characterization. Then, a data categorization scheme was proposed and evaluated. Finally, the impact of the Kalman Filter on the parameter and location estimate were considered with regard to this categorization scheme.

4.1 INCIDENT DATA CHARACTERIZATION

The primary data characterizing parameters are the signal type, the signal category parameter and the Q factor. The distribution data for these parameters are discussed.

4.1.1 Signal Type Distribution

It has been argued that, in the absence of collaborating information, the signal type is a reasonable indicator of the nature of the radiating source. Figure 5 illustrates the signal type distribution among the three major categories, U, E, and I for the 1316 detections. Clearly, more than 60% of the detections are classified as U type signals while less than 5% are classified as I. Because of the nature of the I type signal, and its relative infrequency, it is grouped together with the E type data for statistical purposes.

Therefore, presumably due to the wide variation in the performance of the existing generation of ELT/EPIRBs, only 35% of the signals fall within the norm expected for those radiating as an ELT/EPIRB.

Now, the critical issue for the 380 SAR incidents is that of establishing what information can be derived from the first detection and then, what confirmation information is provided by the second detection. The signal characteristics for subsequent detections become progressively less important since confirmation data is now available from multiple passes.

As will be discussed in Section 4.4, 291 of the 380 SAR incidents involved multiple pass detections or SARSAT confirmations. Table 5 summarizes these 291 cases in terms of signal type for the first detection and then the subsequent signal type on the second detection.

TABLE 5

SIGNAL TYPE - MULTIPLE DETECTIONS

SIGNAL TYPE	FIRST DETECTION	SIGNAL TYPE	SECOND DETECTION
U	165	U	98
		E or I	67
E or I	126	U	71
		E or I	55

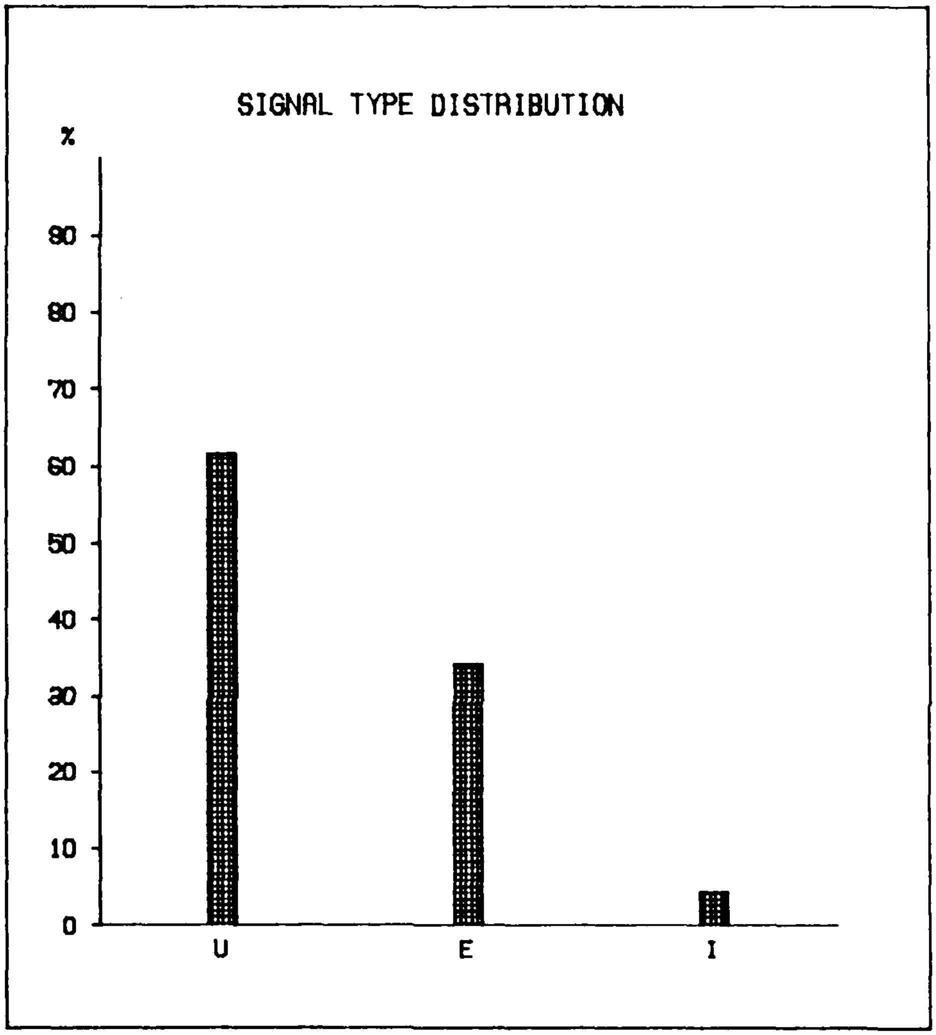


Figure 5: Signal Type Distribution

It is interesting to note that the proportion of U type signals by SAR incident is the same as that noted for detection, i.e. about 60%. Furthermore, this ratio of 6 to 4 carries through to the second detection. It is also evident that, at most, the signal type is a weak ELT characteristic. The signal type classification can change from one pass to the next. Using basic Bayes statistics, it can be inferred from Table 5 that the probability that a U type signal, noted on the first pass, will be classified as a U type signal on the next pass is 0.34. Furthermore, there is a 50-50 chance that the signal type categorization will change from one pass to the next. At this stage of the discussion, these comments do not take into account the quality of the data, e.g. a poor detection on the first pass giving rise to a U type characterization followed by a good detection on the next pass giving rise to an E or I type characterization.

Considerable effort was made to classify the interference type signals as described in Section 3. While they only constitute about 5% of the detections (57 of the 1316 detections), it is felt that operationally, the subcategorization is useful because it indicates a problem or abnormal type signal source. Generally, it can be immediately concluded that any I type signal is a true signal source with identifiable characteristics as noted by the subcategorization. Figure 6 illustrates the observed distribution of the I type signals. About 50% of these signals were F type, just under 40% were N, and the balance were C.

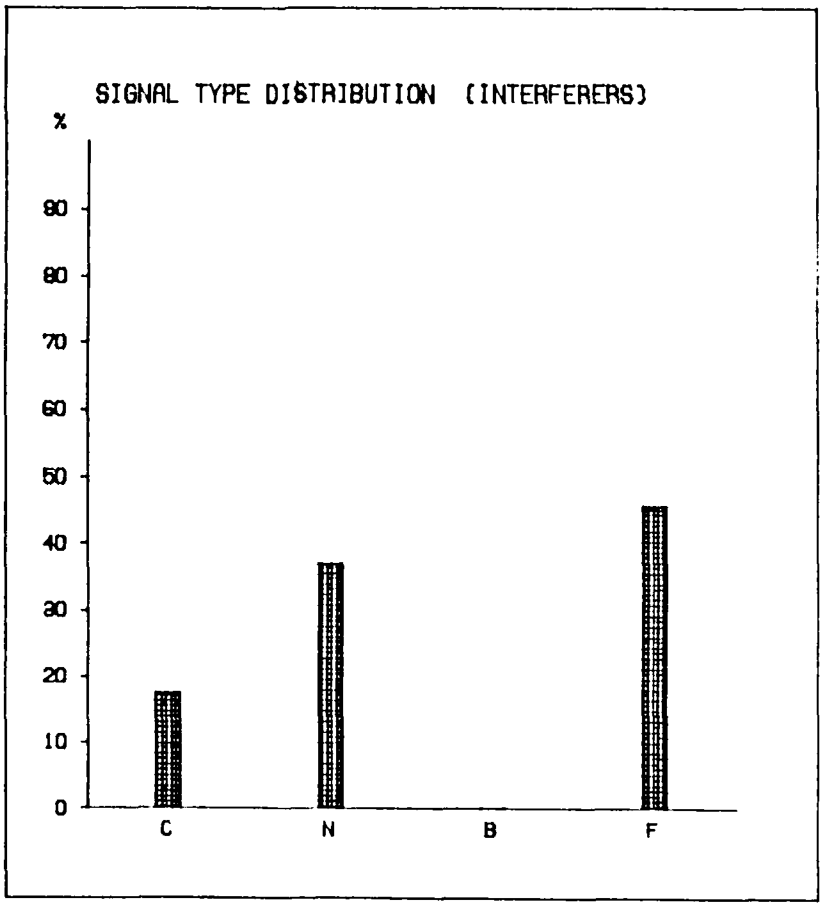


Figure 6: Interferers Distribution.

In summary, it is concluded that the signal type indicator provides a reasonable image of the signal source and does suggest, in a straightforward manner, the nature of the Doppler data used to derive the location estimate. In general, about 60% of the detections will be classified as U type signals, 35% as E type and the remaining 5% as interferers. At most, the signal type is a weak characterizing parameter on a pass-to-pass basis. However, this weakness becomes less significant as confirmation of detection becomes available. The knowledge of the signal type will help indicate to the SAR forces the problems they might encounter on their final homing on the ELT/EPIRB.

4.1.2 Signal Category Distribution

The next parameter of interest is the signal category. It is directly related to the standard deviation of the Doppler curve and therefore is a measure of goodness-of-fit of the signal processing algorithm.

Figure 7 illustrates the distribution of signal category for the 1316 detections in the data base. These data suggest that about 30% of the data is of poor quality, indicative of the nature of the quality of the ELT/EPIRBs SARSAT is expected to locate. In 30% of the cases, the transmission source is of good quality, and the remaining 40% fall somewhere in between. The problem is to recognize the poor quality transmission and then, in quantitative terms, state what this should mean to SAR personnel who have to action the data.

Figure 8(a-c) correlates signal category by signal type. It is obvious that the ordering of signal type by category in terms of poorest to best estimate is U, E and I, a fact noted in previous studies. Therefore it can be concluded that the signal type is a valid indicator of goodness-of-fit and in combination with the signal category parameter can be used to classify incoming detection data.

4.1.3 Q Factor Distribution

The third data quality parameter of interest is the Q factor, the parameter which is indicative of the amount or density of the data.

In a similar approach as taken with the signal category data, Q was plotted for the total data set, and then plotted by signal type. These plots are given as Figure 9 and 10(a-c).

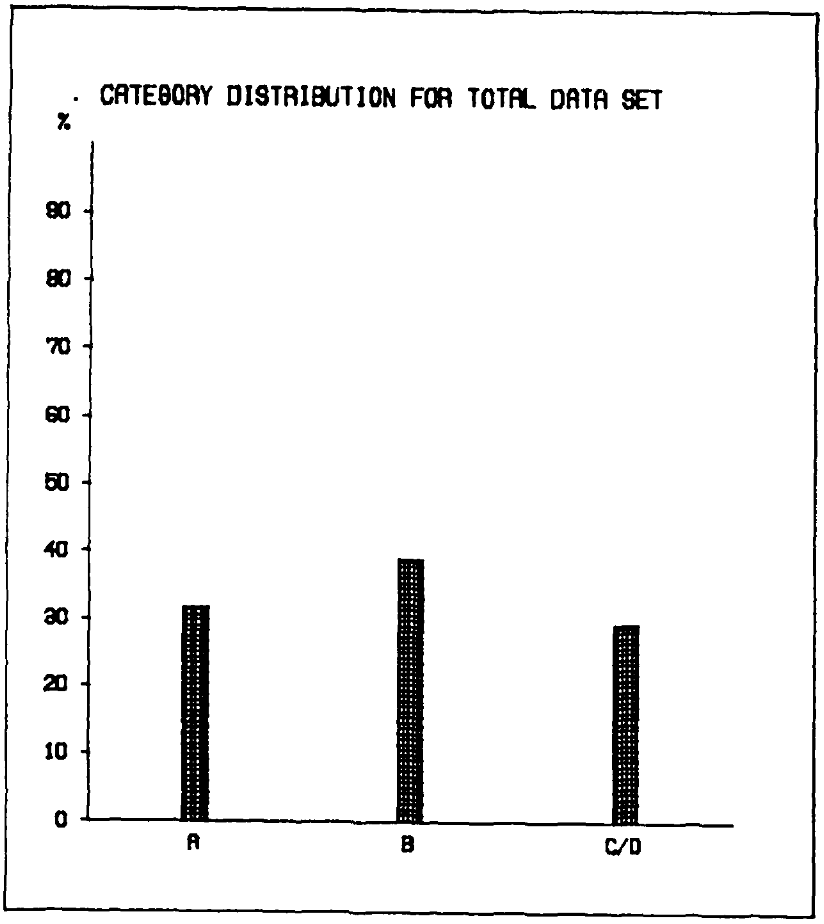
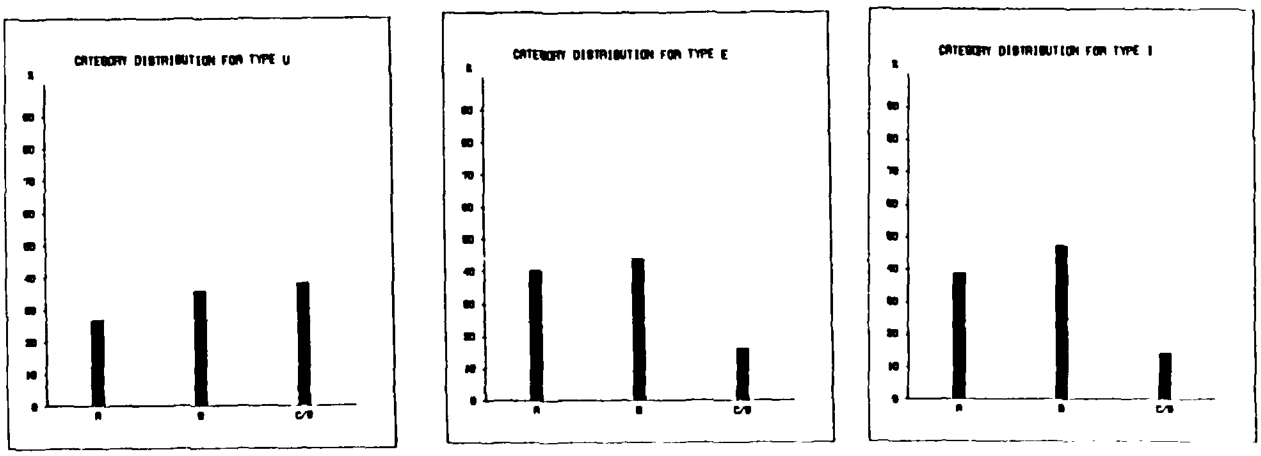


Figure 7: Signal Category



(a) (b) (c)

Figure 8: Signal Category by Type

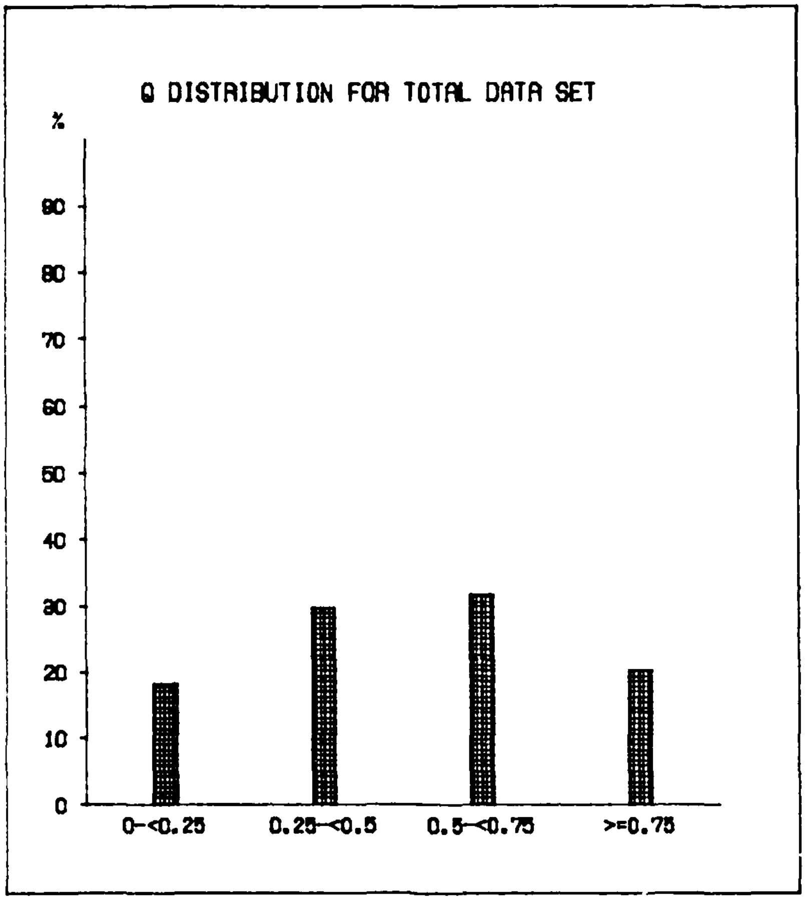
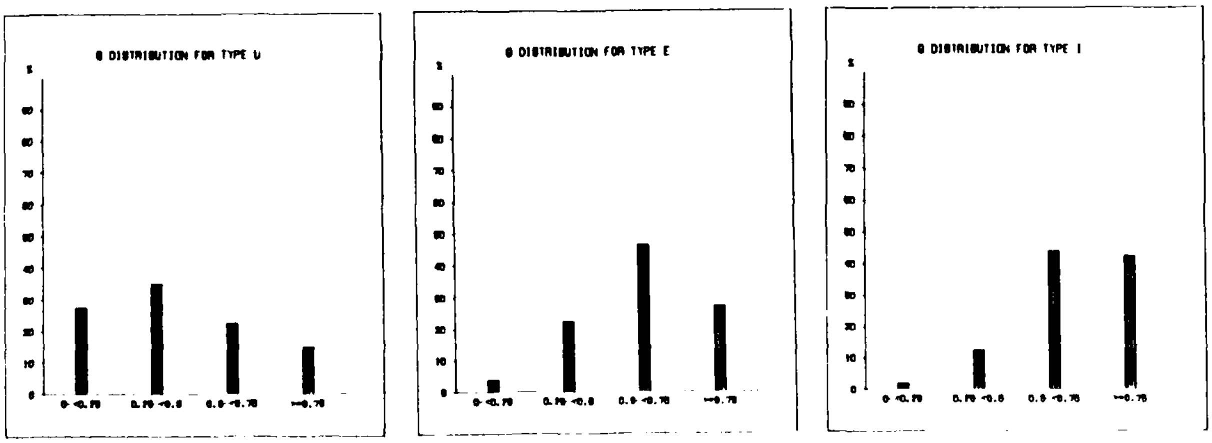


Figure 9: Q Factor Distribution



(b)

(c)

Figure 10: Q Factor by Signal Type

Once again, the poor quality of the transmitting sources is evident. Figure 9 indicates that in almost 50% of the detections, less than one half of the expected data is available. The LUT is working with 75% or more of the expected data in only 20% of the detections.

Figure 10(a-c) suggests the problems associated with identifying the type of signal. With less data, the poorer the signal characterization becomes. It is obvious that the characterization of the signal type is highly dependent on the quality of the incoming signal. This implies that the stronger the signal, the more is the likelihood that sidebands will be above the noise threshold and hence the more likely that the transmission would be categorized as something other than U.

Thus, based on the above argument, there is support to suggest that the type categorization is a good transmitting source characteristic, but that it will only be a consistent characteristic under good detection conditions. Thus for the current generation of ELT/EPIRBs which are very close to the SARSAT detection threshold, inconsistencies will be observed from pass-to-pass as noted in Section 4.1.1. However, it is equally evident that once a signal is identified as a E or I type transmission, it is a good signal and can be actioned with some confidence.

4.2 ACCURACY OF ESTIMATION

It would seem intuitively evident that the location estimate of the ELT/EPIRB would be better for E and I type transmission than for U type signals. Similarily, the smaller the standard deviation and the larger the Q factor, the smaller one would expect the error in location estimation. Furthermore, the SARSAT system is not expected to estimate the location of the ELT/EPIRB with uniform precision for all cross-track angles.

Figure 11(a-d) contain the cumulative error distribution functions for each of parameters discussed above. These diagrams illustrate the parameter definition consistency in terms of location accuracy. The E and I type transmissions are consistently better than the U type transmissions. However, some 30% of the U type transmissions do result in good location estimation. Similarily, 40% of the E and I type transmissions can result in poor estimation.

When the standard deviation is low, e.g. the A category, system accuracy is very good. As noted in Figure 10(b), error increases rapidly as the category goes from B to C/D. In a like manner, the Q factor categories correlate very well with error. In other words, the greater the amount of data, the better the estimation of location. Finally, Figure 11(d) illustrates the impact of CTA on location estimation and tends to validate the choice of CTA "break-points".

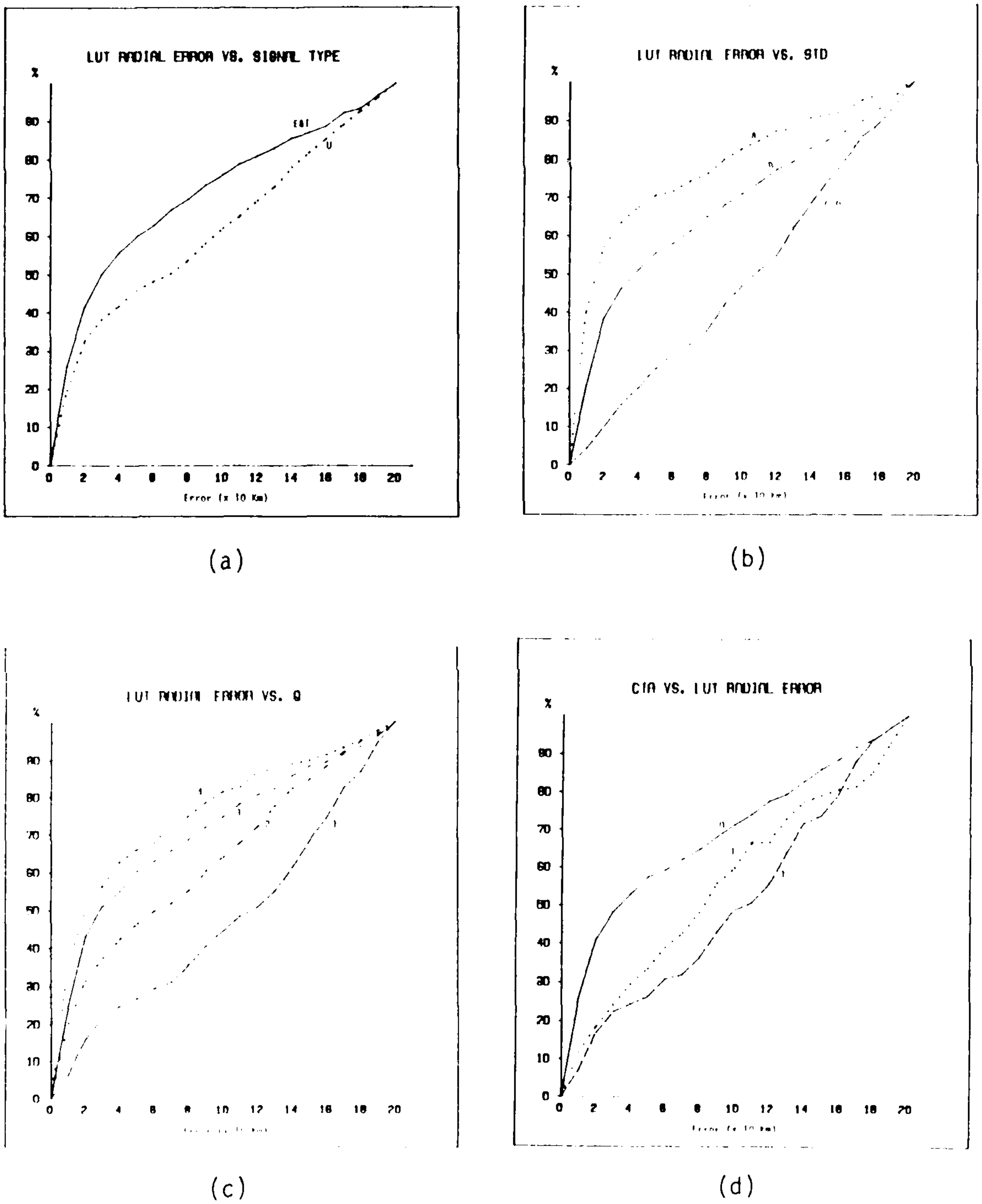


Figure 11: Radial Error Distribution
Functions (x 10 Kilometres)

These distribution functions are characteristic of Rayleigh type distributions as would be expected when using the radial error. There is a high concentration of quality data at the lower end of the distribution with a large spread of poor quality over the long tail of the distribution.

These distributions are characterized in Table 6 in terms of the 50 percentile of the distribution and in terms of the percentile wherein error of location estimation is less than 20 kilometres.

It is obvious from the data given in Table 6 and illustrated in Figure 11(a-d) that system performance cannot be characterized in an simple manner. For example, if operational personnel were to base actioning solely on signal type, i.e. action E and I type transmissions, 35% of the U type transmissions from the SAR incidents have observed error of less than 20 kilometres. Similarily, while the category flag is the best indicator of data quality, good detections, albeit a small percentage, can be made when the category flag indicates poor quality data. Both the Q factor and the geometry flags are good data qualifiers, but as with the above, they cannot be used in isolation.

Therefore, it is concluded that the data quality indicators described in Section 3 are all valid and consistent measures of the performance of the SARSAT system, and they are good indicators of how SAR personnel should interpret and action SARSAT alert data. It is further concluded that in order to interpret the quality of incoming alert data, these parameters should be used in combination. Such a combination is the subject of the discussion in the next section.

TABLE 6

ERROR DISTRIBUTION PARAMETERS VERSUS SIGNAL CHARACTERIZATION

SIGNAL CHARACTERISTIC		NO. IN CLASS.	DISTRIBUTION 50 PERCENTILE (KMS)	PERCENTILE ERROR LESS THAN 20 KM
TYPE	E OR I	507	24.9	45.8
	U	809	64.0	35.3
CATEGORY	A	417	10.8	60.3
	B	512	32.7	42.2
	C/D	387	102.8	12.9
Q FACTOR	4	266	15.6	53.0
	3	418	23.8	47.0
	2	242	56.3	34.4
	1	390	111.7	19.0
CTA FLAG	-1	129	77.5	26.7
	0	1027	28.7	44.6
	1	160	101.7	19.7

4.3 ALERT DATA CATEGORIZATION SCHEME

At Reference (1), a preliminary alert data categorization scheme was proposed. It basically consisted of defining "good" data as that which was classified as being category A or B with a Q factor greater than 0.5. "Bad" data consisted of those alerts observed to have standard deviations in the C or D class and a Q factor less than or equal to 0.5. "Mediocre" data then was defined to be not "good" or not "bad". The criteria for validating this approach was whether the scheme could isolate the alert data by signal type. This is a reasonable approach, but as noted in the previous section, errors in classification can be made.

The current studies have the benefit of the location data associated with the detection. Therefore, the categorization scheme can be developed and quantified in terms of location accuracy.

Using the SAR incident data, the original scheme was modified and the following defintions developed:

Good Estimate: CTA = -1,1 and Category A and Q = 4
or CTA = 0 and Category A or B and Q = 3 or 4.

Mediocre Estimate: CTA = -1,1 and Category A and Q = 3
or CTA = 0 and Category A or B and Q = 1,2

Poor Estimate: Not good and not mediocre

The data in Table 6 and that illustrated in Figure 11(a-d) provide a means of ranking the quality indicators, and this is reflected in the above definitions. Good estimates can be derived under fringe geometry conditions if the signal is strong. If the pass geometry is good, then one still should expect good location accuracy for slightly less stringent goodness-of-fit and data density conditions. Hence the definition of the of the good estimate. The definition of mediocre estimates reflects the ranking of the quality indicators. The category flag reflects good estimation, but the Q factor is down. One is now in the nebulous position of having a good curve match but less data. A poor estimate is then defined as data neither classified good or mediocre. It tends to emphasize the extremes of the scales.

While the alert data categorization scheme given above appears intuitatively logical, it took considerable effort to balance the break points between the three quality parameters.

The validity of the categorization is dependent on two factors. Firstly, does the categorization partition the data base into an acceptable balance? It is futile to categorize the data as all being good or all being bad. Secondly, what does this categorization mean in terms of accuracy?

Table 7 quantifies the partition of the 1316 detections arising from the 380 SAR incidents by signal type according to the alert categorization scheme. The numbers in brackets are the percent breakdowns of the totals by data category.

TABLE 7

ALERT DATA CATEGORIZATION BY SIGNAL TYPE

DATA CATEGORY	U TYPE	E TYPE	I TYPE	TOTAL
GOOD	245 (30%)	262 (58%)	41 (72%)	548 (42%)
MEDIOCRE	185 (23%)	84 (19%)	4 (7%)	273 (21%)
POOR	379 (47%)	104 (23%)	12 (21%)	495 (37%)
	809 (62%)	450 (34%)	57 (4%)	1316

The data in Table 7 suggests that the partitioning of the data by the alert categorization scheme is reasonable and is in reasonable proportions. It only remains to demonstrate that the error distribution functions reflect and validate the scheme, and that poor data is observed (in terms of error) to be poor while good data is in fact good.

Figure 12 illustrates the error distribution functions for the LUT data according to the alert data categorization scheme. Table 8 contains the distribution parameters for the three categories.

TABLE 8

ERROR DISTRIBUTION PARAMETERS BY DATA CATEGORIZATION SCHEME

DATA CATEOGRY	NO. IN CLASS	DISTRIBUTION 50 PERCENTILE (KMS)	PERCENTILE ERROR LESS THAN 20 KM
GOOD	548	13.9	55.6
MEDIOCRE	273	20.3	49.8
POOR	495	96.9	15.6

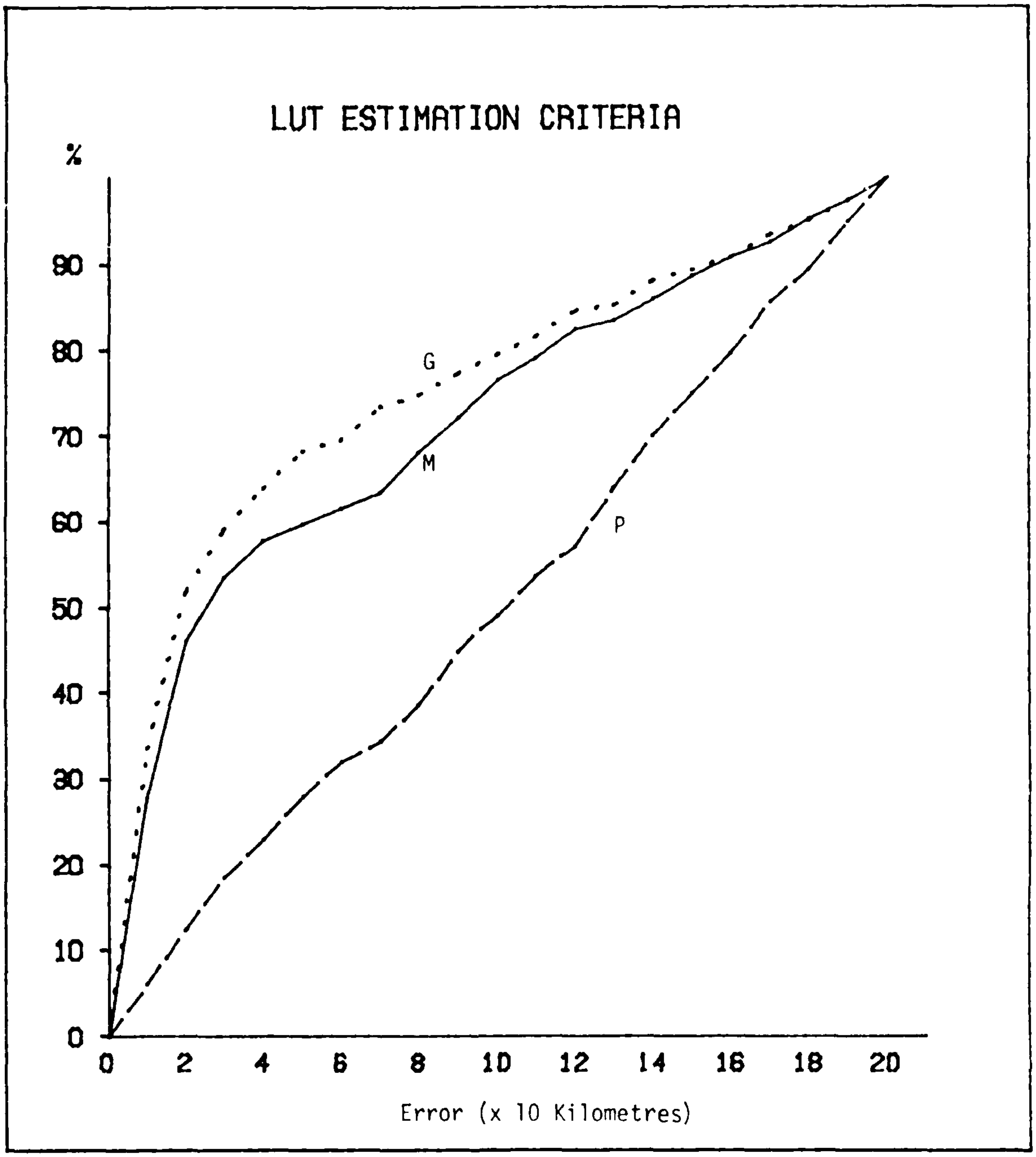


Figure 12: Error Distribution by Data Categorization.

It is apparent that the alert data categorization scheme does in fact isolate out the data according to quality in a consistent manner. The one remaining area to investigate is the impact of the Kalman Filter on the pass-to-pass merge and updating process. This is discussed in the next section.

4.4 IMPACT OF THE KALMAN FILTER - THE CMCC DATA

Thus far, the discussion has concentrated on analyzing the impact of alert data characterization schemes on the SARSAT LUT data. In an operational scenario, SARSAT facilities, in many cases, will detect the transmitting ELT/EPIRB over a number of satellite passes. This gives rise to multiple estimates of location for the same beacon and hence the need for Kalman Filter techniques to combine these estimates to produce a current best estimate of location at any given point in time.

The SAR incident data base consisted of 380 events of which 89 were found to be single detection incidents (based on the Canadian LUT data only). This leaves 291 incidents involving multiple detections. The distribution of the number of merges is illustrated in Figure 13. As noted above, about one quarter of the incidents were single detections and approximately 25% involved only one additional detection. Therefore 50% of the incidents involved two or more detections.

The single detection incidents consisted of 51 U type signals, 34 E type signals and 4 I type signals. In proportional terms, 60% were U and about 40% were E or I, the common partition noted previously. Since these data contribute nothing to the understanding of the impact of the Kalman Filter, they were ignored and the analytical effort was concentrated on the remaining 219 incidents involving 1,227 detections.

Figure 14 illustrates the error distributions for the LUT and the CMCC (or filtered data) not taking into account the conditions of the detections. Not surprisingly, the CMCC data provides a better overall estimate of the location of the ELT/EPIRB. Furthermore, as would be expected, the filter does little to improve good data and is incapable of correcting poor data. Its most significant impact is in the region when error of estimation is in the range 20-100 kilometres. In this range, the Kalman Filter can reduce error in the order of 12%, again not taking into account the conditions of the detection. Table 9 contains the parameters of the two distributions.

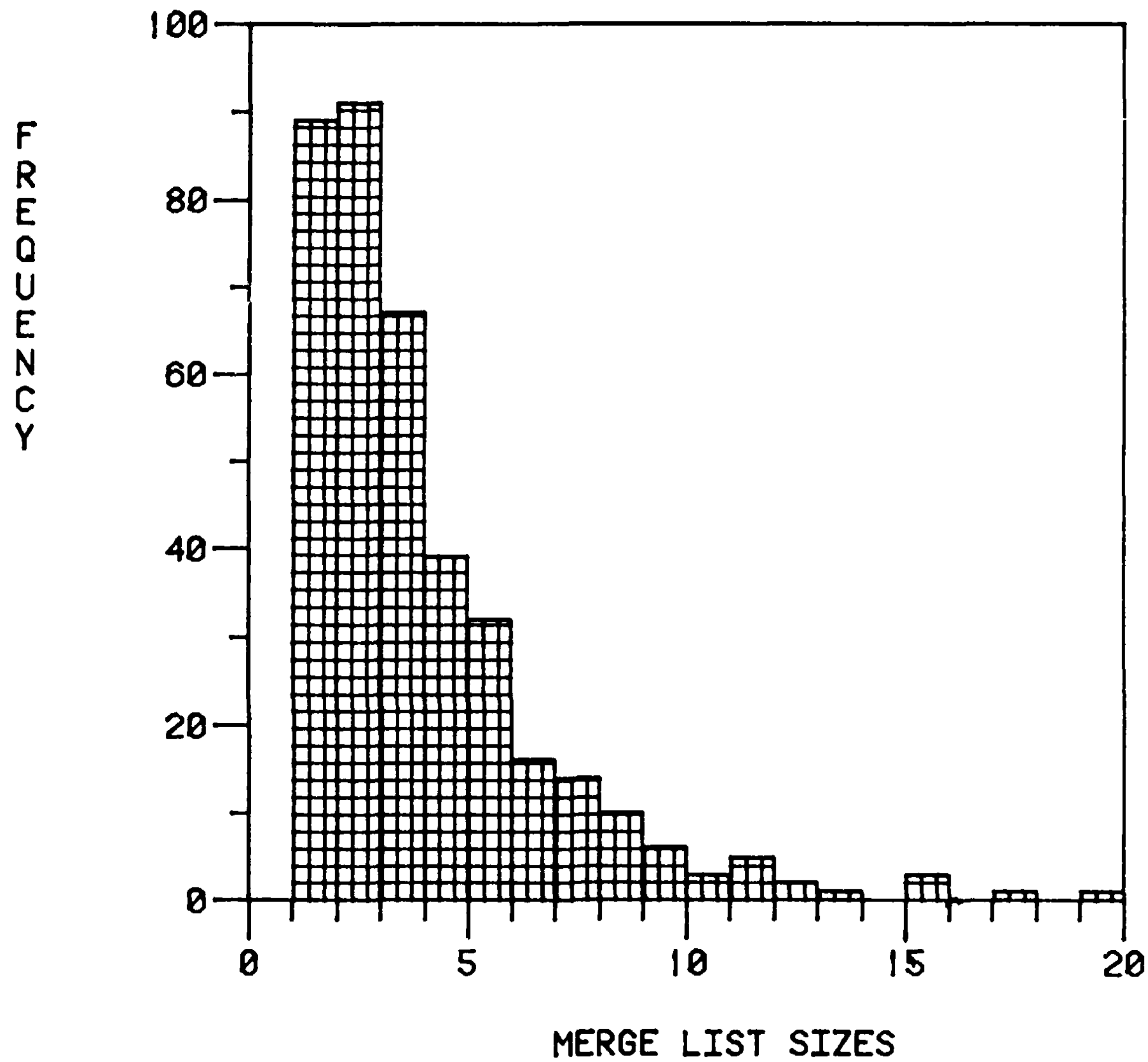


Figure 13: Merge No. Distribution.

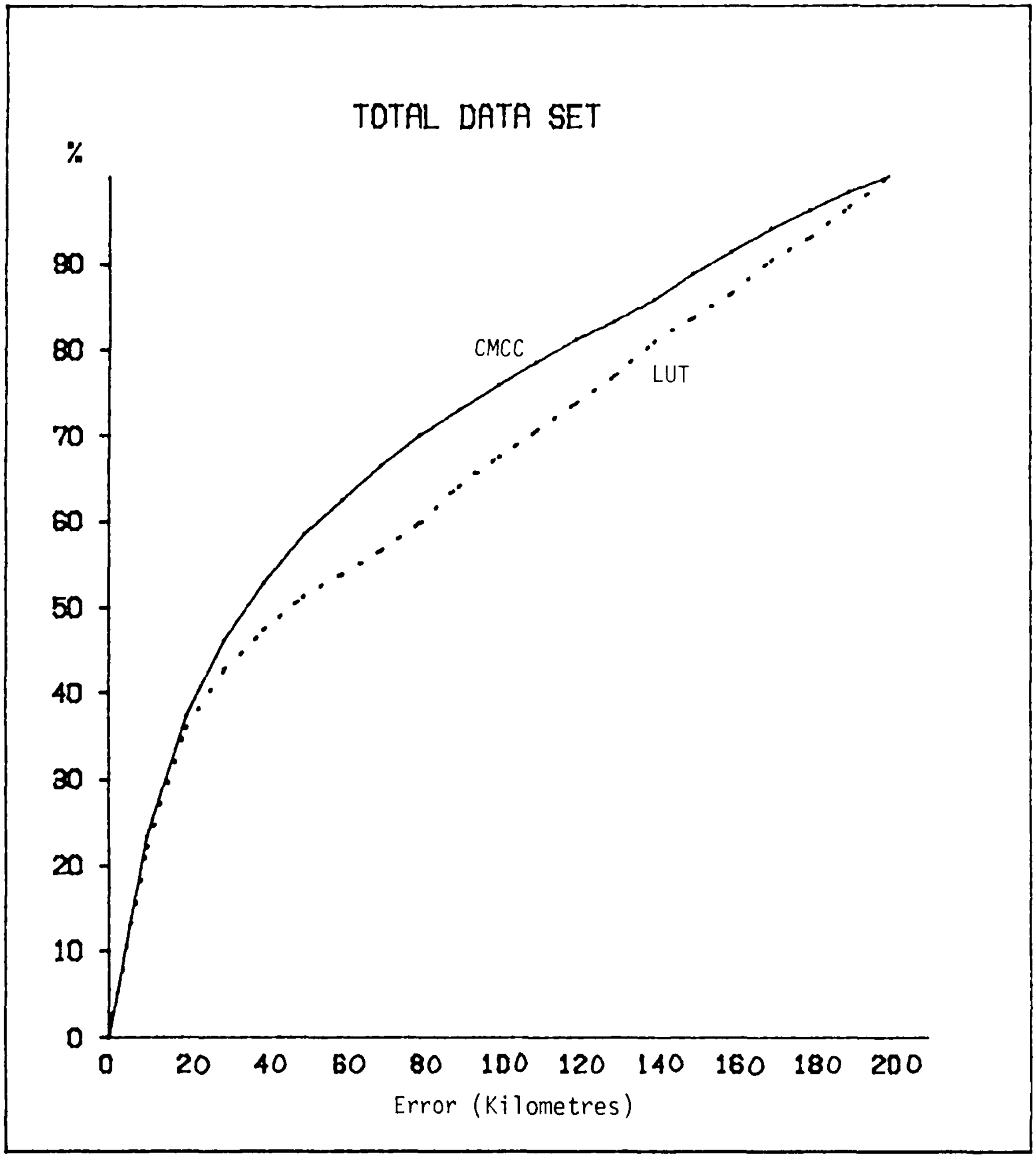


Figure 14: Error Distribution
CMCC and LUT Data

TABLE 9

ERROR DISTRIBUTION PARAMETERS FOR CMCC AND LUT DATA

DATA DISTRIBUTION	DISTRIBUTION 50 PERCENTILE (KMS)	PERCENTILE ERROR LESS THAN 20 KM
CMCC	30.9	41.7
LUT	41.8	39.3

At the distribution 50 Percentile, accuracy of location can be improved by about 10 kilometres. However, as noted above, for good location estimates, e.g. error less than 20 kilometers, the improvement is small.

Figure 11 and Table 6, see Section 4.2, contained the error distribution parameters categorized by signal characteristics, i.e signal type, category, Q factor and CTA. Table 10 contains the same data as well as the data calculated for the CMCC distributions.

TABLE 10

ERROR DISTRIBUTION PARAMETERS
VERSUS
SIGNAL CHARACTERIZATION (CMCC & LUT)

SIGNAL CHARACTERISTIC		DISTRIBUTION 50 PERCENTILE (KMS)			PERCENTILE ERROR LESS THAN 20 KMS		
		CMCC	LUT	Δ	CMCC	LUT	Δ
TYPE	E OR I	24.9	24.9	0.0	45.2	45.8	-0.6
	U	35.9	64.0	-28.1	39.5	35.3	4.2
CATEGORY	A	13.2	10.8	2.4	57.1	60.3	-3.2
	B	33.5	32.7	0.8	39.8	42.2	-2.4
	C/D	52.0	102.8	-50.8	27.5	12.9	14.6
Q FACTOR	4	19.2	15.6	3.6	50.6	53.0	-2.4
	3	24.3	23.8	0.5	45.8	47.0	-1.2
	2	35.6	56.3	-20.7	38.8	34.4	4.4
	1	54.3	111.7	-57.4	29.3	19.0	10.3
CTA FLAG	-1	51.2	77.5	-26.3	27.9	26.7	1.2
	0	27.3	28.7	-1.4	44.0	44.6	-0.6
	1	42.5	101.7	-59.2	37.8	19.7	18.1

These data further emphasize that which was stated previously. The filter, as expected, does little to improve quality data but has a significant impact on the poorer quality detections. In some of the signal characteristic categories, the quantitative improvement is quite major. Figure 15(a-d) contains the error distribution plots of the filter data for each of the data quality parameters.

The one remaining item to illustrate is the impact of the filtered data on the alert data characterization scheme. Table 11 summarizes the error distribution parameters for the CMCC and the LUT data for the categorization scheme defined in Section 4.3.

TABLE 11

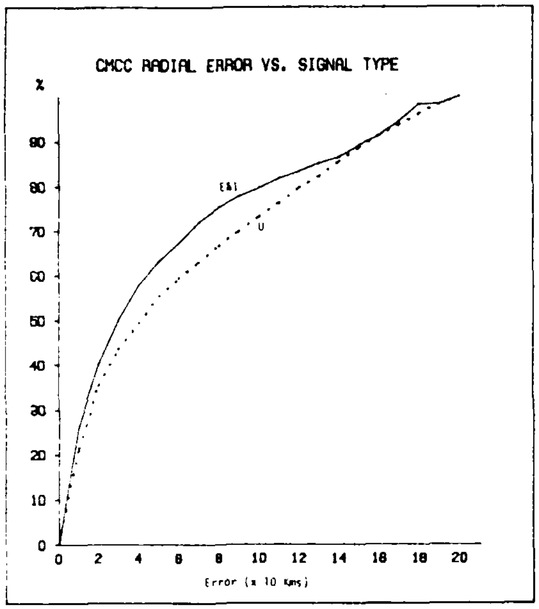
ERROR DISTRIBUTION PARAMETERS BY DATA CATEGORIZATION SCHEME
FOR CMCC AND LUT DATA

DATA CATEGORY	NO. IN CLASS	DISTRIBUTION 50 PERCENTILE (KMS)			PERCENTILE ERROR LESS THAN 20 KMS		
		CMCC	LUT	Δ	CMCC	LUT	Δ
GOOD	548	18.0	13.9	4.1	51.7	55.6	-3.9
MEDIOCRE	273	25.8	20.3	5.5	45.2	49.8	-4.6
POOR	495	50.7	96.9	-46.2	28.6	15.6	13

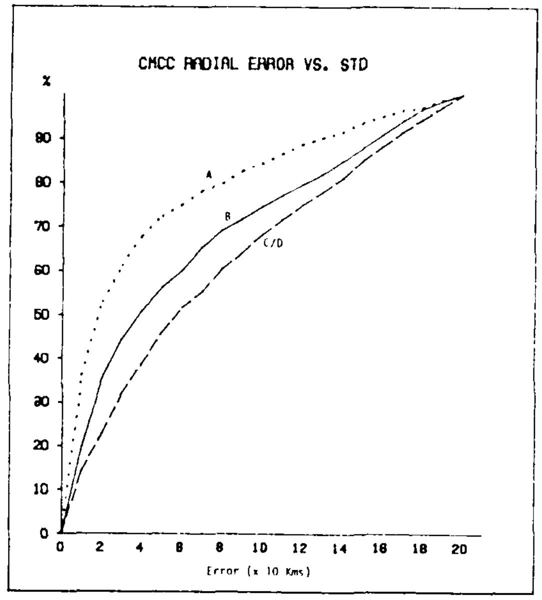
Again, the impact of the Kalman Filter is evident. It has little, or to some extent, a negative impact of good and mediocre classified data but a major impact on the poorer quality data. At the distribution 50 Percentile, for the poor quality data, one is looking at improvements in the order of 50 kilometres. Furthermore, the number of poor quality detections with observed errors of less than 20 kilometres has doubled.

Figure 16 contains the error distribution functions for these data in terms of the alert categorization scheme definitions. If one compares these data to that given in Figure 11, it is readily apparent that the data distributions for the good and mediocre data is essentially the same (the impact of the filter is to smooth the distribution curve) while that for the poor category is altered and improved significantly. The differences between these two distributions is illustrated in Figure 17.

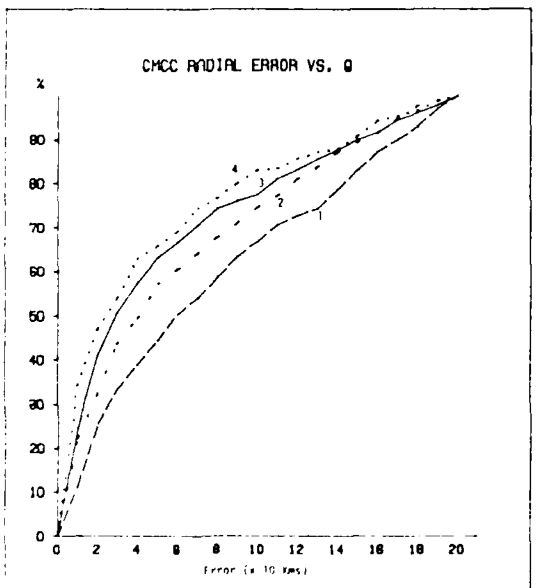
In summary, it is evident that the Kalman Filter significantly improves the accuracy of estimation of the detections derived by the SARSAT LUT. This improvement, overall, is insignificant if the original estimates were of good quality. However, major improvement is noted from poorer quality estimates, and since about 40% of the SARSAT data fall into this latter category, the importance of filtering the data cannot be understated.



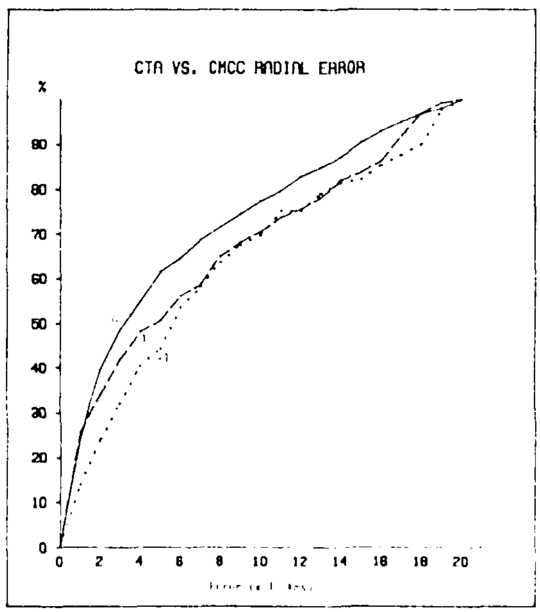
(a)



(b)



(c)



(d)

Figure 15: Radial Error Distribution Functions (x 10 Kilometres)

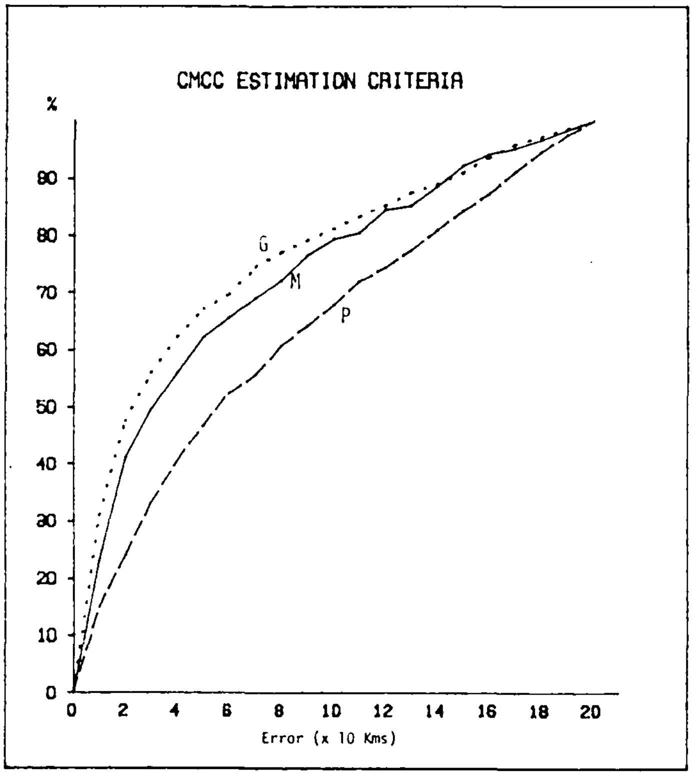


Figure 16: Error Distribution
CMCC Data by Category

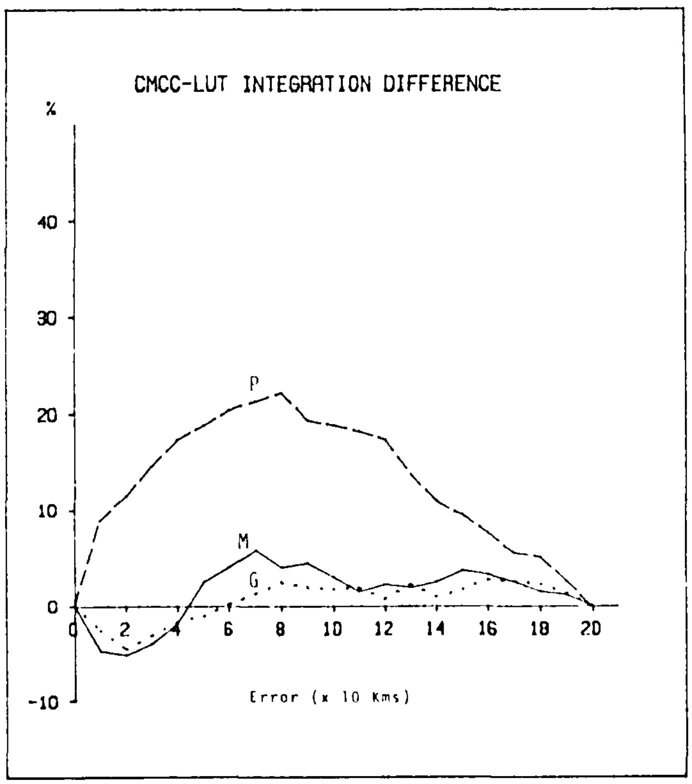


Figure 17: Difference in CMCC-LUT
Error Distributions

5.0 DISCUSSION OF RESULTS

As a result of the approaches outlined in Section 4, it is evident that the SARSAT facilities can better support the user and can provide significant guidance on how best to action the ELT/EPIRB alert data. This guidance comes through a judicious use of existing data.

The issue in Section 4 was to be able to identify or categorize alert data in a meaningful manner so that the SAR user has sufficient information to make a reasonable and balanced decision on whether to respond immediately to the data or to await further information. In summary, definitions can be used to distinguish good, mediocre and poor SARSAT data. The question is how best to action the data given the type of signal detected and the quality of the signal.

In the following discussion, rules for actioning the alert data are outlined and the impact of using this approach is analyzed through the application of these rules to the 380 SAR incidents which formed the study data base.

Table 12(a) categorizes the first detection for the 380 SAR incidents by signal type according to whether the data quality was observed to be good, mediocre or poor. These data are presented in terms of whether the transmission was seen once or on subsequent passes.

Firstly, it is agreed that all data categorized as good or mediocre is actionable immediately. Referring to Table 8 and Figure 12, more than 50% of these data should exhibit errors of estimation of less than 20 kilometres. This accounts for 58% of the SAR cases. It is further suggested that an additional 47 cases, or 12%, warrant immediate SAR action. These are the poor quality E and I type signals. The signal type categorization conveys the fact that a real transmission has been detected while the classification of the quality suggests the error in location estimation is large. Therefore, the specific SAR response would be qualified. The data is sufficient to warrant communication checks but not of good enough quality to immediately consider resource expenditure. In summary, using the SAR incident data to establish order of magnitude estimates, 70% of the 380 incidents can be actioned on the first detection, 58% without qualification and an additional 12% with the qualification that the location estimate is quite poor.

The remaining 30% of the detections require additional information before any SAR action can be taken. These are the U type of signals of poor quality. As is illustrated in Table 12(a) 24 incidents involving a single Canadian SARSAT detection fall within this category. These 24 incidents or 6% of the cases can not be actioned without the aid of external information, e.g. from conventional SAR detection means or from USA SARSAT sources.

TABLE 12(a)

SAR CASES - FIRST DETECTION CATEGORIZATION

DATA CATEGORY	SINGLE DETECTION SIGNAL TYPE U	E	I	MULTIPLE DETECTION SIGNAL TYPE U	E	I	TOTALS
G	14	22	2	43	62	8	151
M	13	4	0	32	18	1	68
P	24	8	2	90	36	1	161
	51	34	4	165	116	10	380

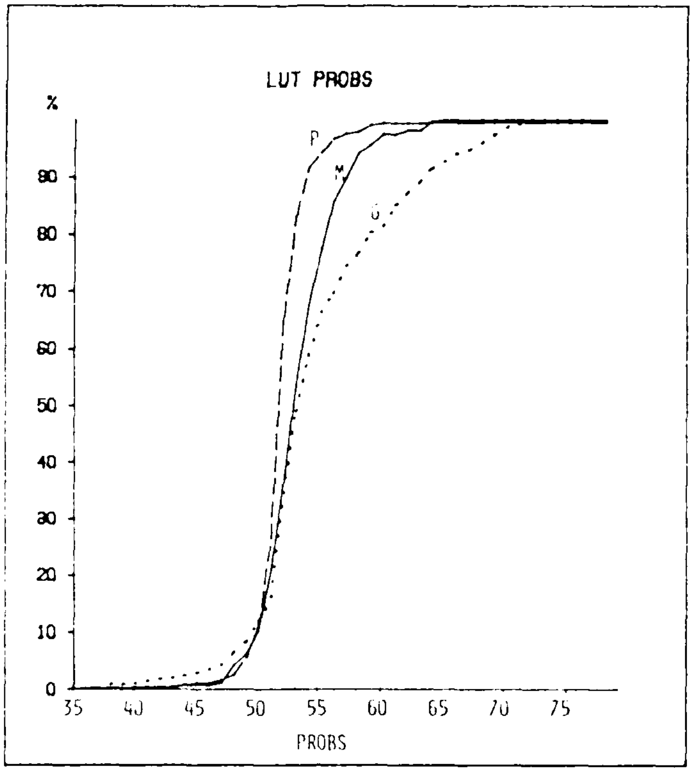
TABLE 12(b)

SECOND DETECTION
ON FIRST DETECTION, SIGNAL TYPE U AND CLASS P

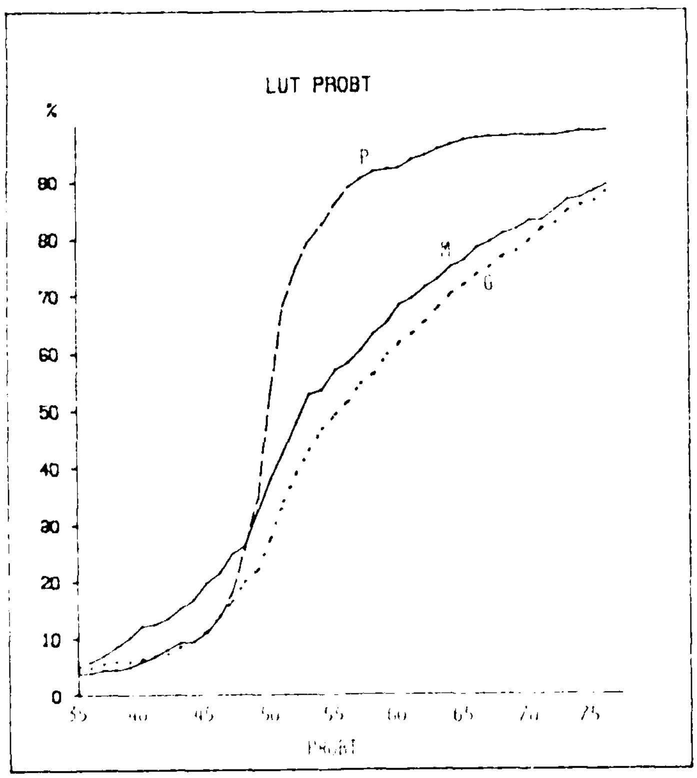
DATA CATEGORY	SIGNAL TYPE U	E	I	TOTALS
G	12	27	0	39
M	6	8	0	14
P	31	4	2	37
TOTALS	49	39	2	90

Table 12(b) considers the remaining 90 incidents or 24% of the cases. These are the U type signals known to be detected on a subsequent satellite pass. On the second detection, 59 of the events now meet the standard necessary for actioning. Only 31 incidents or 8% of the cases fall into the category of a U type signal of poor quality on the first detection and remaining that way through the second detection. All that can be said about these incidents is that they are confirmed events, but that the ELT/EPIRB is of such poor quality, SARSAT can not precisely locate it.

Figure 18(a-b) illustrates the ambiguity resolution capability of SARSAT for the alert categorization scheme based on the incident data. Ambiguity resolution is plotted for PROBS, (based on standard deviation) and for PROBT. The latter is derived from the LUT Trend Factor. Table 13 contains the distribution percentile by category for PROBS and PROBT equal to 50. The percentile greater than 50 indicates the probability of ambiguity resolution.



(a)



(b)

Figure 18: Ambiguity Resolution
by Data Categorizations

TABLE 13

AMBIGUITY PROBABILITY RESOLUTION
BY ALERT CATEGORIZATION

DATA CATEGORY	PROBS PERCENT $\geq$ 50	PROBT PERCENT $\geq$ 50
GOOD	65.5	72.2
MEDIOCRE	63.0	67.4
POOR	34.3	46.9

It is apparent that good ambiguity resolution is available with good and mediocre data. The PROBT form of ambiguity resolution tends to enhance the resolution scale. There is very little capability to resolve ambiguity when the alert data is categorized as poor.

In summary, it is proposed that procedures can be established to action SARSAT alert data based on available data qualifiers. Using the SAR incidents which occurred during the SARSAT D&E as a basis for the development of these procedures, it is suggested that the following approaches seem reasonable. All data categorized as good or mediocre are actionable upon receipt. Furthermore, the probability is relatively high that ambiguity can be resolved on the first pass. It should be recognized that E and I type transmissions of poor quality are valid transmissions and warrant attention. However there is only a small probability that, in this case, ambiguity can be resolved on the first pass. About 30% of the SAR incident alert data must await further information. They are not of sufficient quality to warrant action without collaborating information. In the case of the SAR incidents, SARSAT provided this information for one half of these incidents on a subsequent pass. Of the remaining incidents, one half were not detected again and the other half continued to demonstrate poor quality. In total, 85% of the SAR incidents in the study data base were resolvable by the second detection.

6.0 SUMMARY COMMENTS AND RECOMMENDATIONS

It is concluded that SARSAT system performance can be improved significantly if the SAR users are given more support and guidance on how to interpret beacon alert data. Alert data categorization schemes can be developed from existing LUT parameter data which could facilitate this interpretation.

An analysis of the SAR incidents which occurred during the SARSAT D&E has demonstrated the capabilities of one such categorization scheme. It seems to work quite well. In hindsight, it is viewed as an intuitatively obvious categorization and hence is probably quite a conservative approach.

It should be noted that the approaches suggested are based on a statistical analysis of highly variable data. The observed operational ELT/EPIRB performance is far from good. Therefore, one can expect instances where the data categorization scheme will work much better than suggested but also there will be instances where it will perform quite poorly. These conclusions necessarily do not take into account the positive support that is available from conventional SAR sources.

In conclusion, it is recommended that the SARSAT alert data categorization scheme developed as a result of the analysis of the SAR incidents which occurred during the SARSAT D&E, be considered for implementation in future Canadian SARSAT facilities.

7.0 REFERENCES

1) W.R. McPherson & S.Y. Slinn, "SARSAT LUT to CMCC Alert Data Interface, A Critical Review". DREO Technical Note 84-24, December, 1984.

2) "COSPAS-SARSAT Project Report", COSPAS-SARSAT Coordinating Group. August, 1984.

3) H.L. Werstiuk, "COSPAS-SARSAT: A System Overview". Proceedings I.E.E.E., 1983, Vol. 1, pp 168-171, Paper No. 83071.

4) S.Y. Slinn and W.R. McPherson, "SARSAT-LUT and CMCC Simulation Package, Program Description". DREO Technical Note 85-17, April, 1985.

5) W.R. McPherson, B.W. Kozminchuk and S.Y. Slinn, "Canadian COSPAS-SARSAT Demonstration and Evaluation Results - Final Report". DREO Report 930, July 1985.

6) S.Y. Slinn, "LOCAT - A Data Retrieval Program". DREO Technical Note 84-30, December, 1984.

7) James D. Taylor and Richard C. Renner, "Canadian Astronautics Limited's SARSAT Ground Stations". Proceedings, Symposium on *Satellite Aided Search and Rescue, Experimental Results and* Operational Prospects, Toulouse, France, April 1984, pp. 169-182.

UNCLASSIFIED

Security Classification

DOCUMENT CONTROL DATA R & D

ORIGINATING ACTIVITY Defence Research Establishment Ottawa Department of National Defence Ottawa, Ontario K1A 0Z4	DOCUMENT SECURITY CLASSIFICATION UNCLASSIFIED GROUP

DOCUMENT TITLE

SARSAT OPERATIONAL DATA CATEGORIZATION AND ACCURACY STUDIES

DESCRIPTIVE NOTES (Type of report and inclusive dates)

TECHNICAL NOTE

AUTHOR(S)

McPHERSON, W. Roy and SLINN, Suzanne Y.

DOCUMENT DATE SEPTEMBER 1985	7a. TOTAL NO. OF PAGES 42	7b. NO. OF REFS 7
PROJECT OR GRANT NO. 33X00	9a. ORIGINATOR'S DOCUMENT NUMBER(S) DREO TECHNICAL NOTE NO. 85-26	
CONTRACT NO.	9b. OTHER DOCUMENT NO.(S) (Any other numbers that may be assigned this document)	

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ABSTRACT

The definition of what data is transferred from the SARSAT ground tracking station to operational search and rescue users influences how well the users can action beacon alert data. Based on an evaluation of operational search and rescue incident data collected during the SARSAT Demonstration and Evaluation, categorization and accuracy studies described herein indicate that methodologies can be developed which will significantly improve the operational actioning of SARSAT generated beacon alert data. The results of these studies are presented and recommended approaches to the handling of SARSAT data are given.

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12. SPONSORING ACTIVITY: [illegible] development. [illegible]

13. ABSTRACT: [illegible]

14. KEY WORDS: [illegible]

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8-86